UNIABUJA Journal of Engineering and Technology
https://ujet.uniabuja.edu.ng/
ISSN: 2714-3236 (Online); 2714-3228 (Print)
Volume 2, Issue 2, 2025; 273-286

Deep Learning Approach for Feature Recognition and Extraction in Computer-Aided Process Planning and Manufacturing: Current State and Future Directions

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Abstract
With the global rise in demand for various parts products, manufacturing industries must adopt modern manufacturing approaches to achieve customer satisfaction, timely production, reliability and cost-effectiveness. Features have been the distinguishing attributes of components; these attributes require adequate recognition and careful planning to ease production lag times. Computer-Aided Process Planning transforms these features from design specification through Computer-Aided Design model into manufacturing sequences for a computer-aided manufacturing system. This review paper highlights the deep learning approach adopted to aid computer-aided process planning methodologies in feature extraction and recognition, and proposes the potential of using deep learning methodologies in feature recognition, extraction, and specification using convolutional neural networks, it also presents future directions for further study.

Keywords: *Convolutional neural networks, computer-aided design, process planning, feature recognition, manufacturing, bibliometric analysis, VOS Viewer, Deep Learning.*

1.0 Introduction

Machining is a process that involves the removal of chips from an element through either turning, milling and other operations or modern methods, to create elements (products) with specified dimensions, while taking accuracy and surface roughness as paramount to the detailed drawings. Although machining has made it possible to produce complicated components of different shapes and sizes, machining operations require operators with several years of experience. Therefore, parts machining processes using conventional tools and methods are cumbersome, time-consuming and hence expensive (Rafał, Piotr, & Adam, 2019).

By the year 20250, the global population is estimated to surpass 10 billion, which will bring about a huge increase in demand for food, raw materials, and other essential finished products. Traditional approaches and market productivity must be reimagined, highly competitive measures must be adopted, and used by manufacturers to produce components with low lead time, cheap, reliable, cost-effective, uniform accuracy, improved quality of work pieces and increased flexibility in production, to meet the ever-demanding customer preferences (Yang, Kumara, T.S., Bukkapatnam, & Tsung, 2019), (Nurudeen, Dagwa, & Muhammad, 2020).

Computer-aided Process Planning (CAPP) plays a vital role in the management of industrial operations, ensuring the efficiency of manufacturing industries (Nwasuka & Nwaiwu, 2024). Companies need to have a dynamic service approach that delivers a variety of options with reduced cycle time and product complexities (Dios & Framinan, 2016). The use of Deep Learning (DL) in CAPP is reshaping the practice of process planning and control. The methodologies enable the use of algorithms and machine learning models to analyse real-time data and optimise production processes (Buer et al., 2021). This data-driven approach through careful analysis of data collection is vital in improving efficiency, precision and decision-making and integration with practical knowledge (Asghar et al., 2024).

The information stored in the Numerical Control (NC) machines' part programs is mostly left dormant in NC machining (Zhang et al., 2013). The absence of systematic data in process planning can lead to negative challenges, especially in re-manufacturing situations (Xu et al., 2011). Planners are known to use pre-existing process information to protect machining knowledge, to increase reliability, and to improve product creation (Asghar et al., 2024). CAPP technologies are essential in creating and verifying part programs, although there are limitations to their integration with NC machines; as such, the need for adopting data-driven technologies of deep learning to provide models that adopt a pre-existing knowledge database to learn and create effective design processes(Dannen et al., 2024).

The purpose of this paper is to present the methodological concept of Deep Learning and Computer-aided Process Planning, an analysis of existing publications to serve as a basis for the review, highlighting the advances through research and suggesting future directions. Categorised into six sections; section one serves as the introductory aspect of the review, section two highlighted the review methodology, section three discusses bibliometric analysis, section four discusses CAPP and its methodologies; section five explains what Deep learning is, functions, implementation tools, training of CNN and applications of CNN; section six discusses future directions and finally section six presents the concluding remarks of the study.

2.0 Methodology

The methodology adopted for this review is the Preferred Reporting for Systematic Reviews and Metal-Analyses (PRISMA). This structure provides a synthesis of the state-of-the-art in a field, through which future research niches can be identified and address issues that individual studies could not answer, it also generates various knowledge for different readers (Page et al., 2021).

2.1 Bibliometric Analysis

The bibliometric examination of sources was done focusing on DL within the CAPP framework. The current research and advancement of DL and CAPP was analysed through review papers and scholarly articles. This further simplifies the process of literature search and enables thorough examination of research theories and collaborative networks with the field through analysis of citations trends, co-authorship relations, country and organization of research as well as source of funding of the research amongst others.

Co-authorship, citations, organisation and country classification maps were generated to highlight the relationship between studies, authors and topics using VOS viewer software to automatically showcase occurrences and co-occurrence matrices, clustering of related researches through detailed maps of how DL is integrated into CAPP.

A total of 149 papers were chosen during the literature review screening process consisting of 94 articles, 39 conference papers, 11 reviews, 2 book chapters, 1 note and 1 short survey.

2.2 Content Analysis

This section explores the meticulous review and systematic organisation of substantial information, like scholarly articles and conference papers, in order to understand the themes and patterns of deep learning to CAPP as shown in Figure 1. Which shows the publication patterns of papers related to DL and CAPP over six-year span.

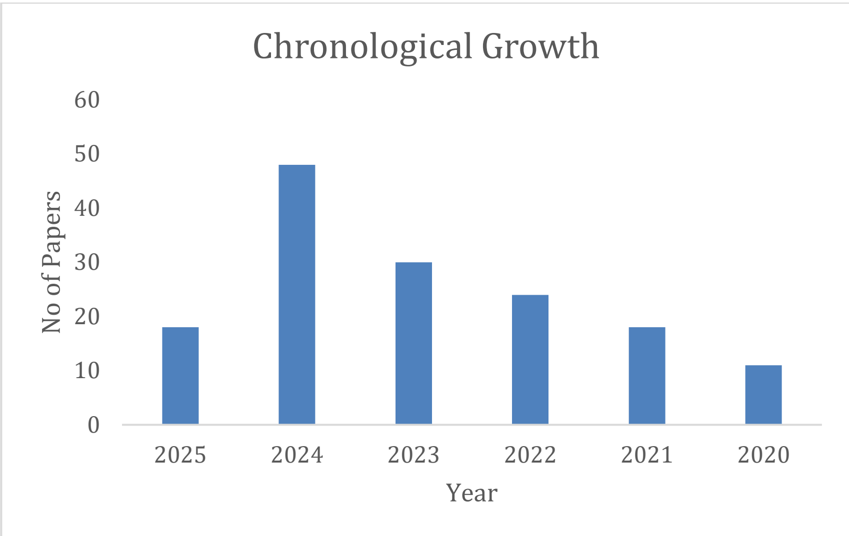

Figure 1: Publications about Deep Learning and CAPP

3.0 Bibliometric Analyses

3.1 Co-occurrence map based on text data

Through the analyses of 149 publications, selected through literature screening process, relevant and frequently occurring terms were identified. The focus was on the titles and abstracts of these publications to extract significant terms and develop a network of co-occurrence links among the articles. This process made it possible to highlight emerging developments and explore the most influential terms of deep learning and CAPP applications.

The data were processed using VOS VIEWER, a total of 1845 terms were generated and 110 terms were selected based on a minimum occurrence threshold of 5. Terms with high relevance scores were indicative of more specific topics within the data, while terms with lower relevance scores were generally associated with broader concepts (Alghazo et al., 2025). The results, as demonstrated in Figure 2, reveal a wide variety of research areas in which deep learning is employed, showing a broad spectrum of interconnected networks of key terms that deep learning encompasses.

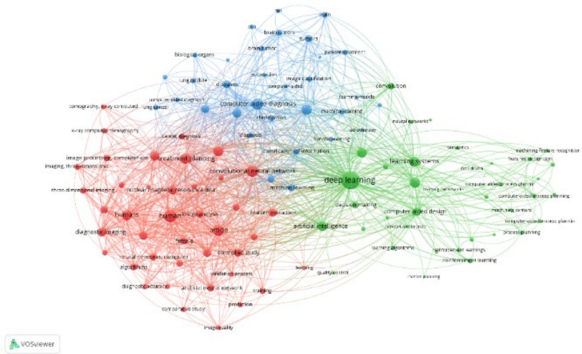

Figure 2: Co-occurrence map based on text data

As indicated in Figure 2, various clusters reveal the connections between different themes, the green clusters focus on "deep learning" which is closely associated with several key terms, including "computer-aided process planning", "convolutional neural networks", "machine feature recognition", and "learning systems". This reiterates the focus on CAPP methodologies indicating that deep learning and related technologies plays a vital role in advancing CAPP applications.

Furthermore, Figure 3 showcases a detailed view of the connection "deep learning" has with other terms such as "machine feature recognition", "image processing", "convolutional neural networks". The red cluster focusses on process planning themes such as "feature recognition", "deep reinforcement learning", "computer-aided design", "process planning" among others, underscoring on the deep learning approaches within CAPP. While terms like "training ", "feature extraction", "classification", "segmentation" in the blue cluster suggests methods used in developing feature recognition and extraction in CAPP through deep learning methodology.

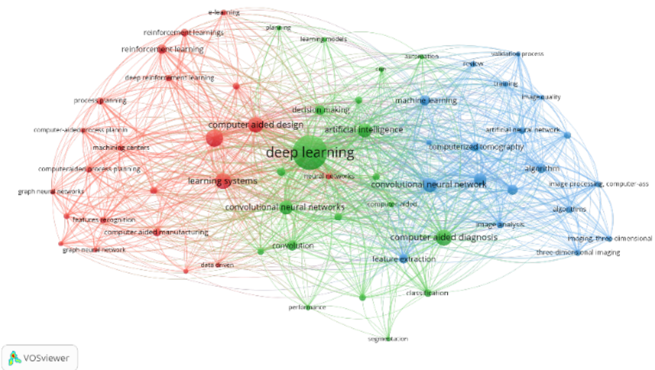

Figure 3: Co-occurrence map based on keywords

In all, images shown in Figures 2 and 3, "deep learning" appears as the central node with numerous connections extending to related terms, further demonstrated its broader impact across various areas in engineering as can be seen in the blue and red clusters.

The visualisation highlights the role of deep learning in advancing feature extraction and recognition through CAPP approaches, which serve to simplify manufacturing processes. Future researchers can use this map to explore other areas and identify emerging topics that may benefit from future research, such as Computer-aided Design (CAD), Computer-aided Manufacturing (CAM). Figures 2 and 3 present a comprehensive overview of how deep learning intersects with several manufacturing themes with academic and industrial applications to CAPP, making it a valuable tool for understanding the scope and focus of current research in the field.

Table 1: Breakdown of Document Type and Citations

Document Type	Count of Source title	Sum of Cited by
Article	97	1500

Document Type	Count of Source title	Sum of Cited by
Book chapter	2	6
Conference paper	37	182
Note	1	1
Review	11	295
Short survey	1	28

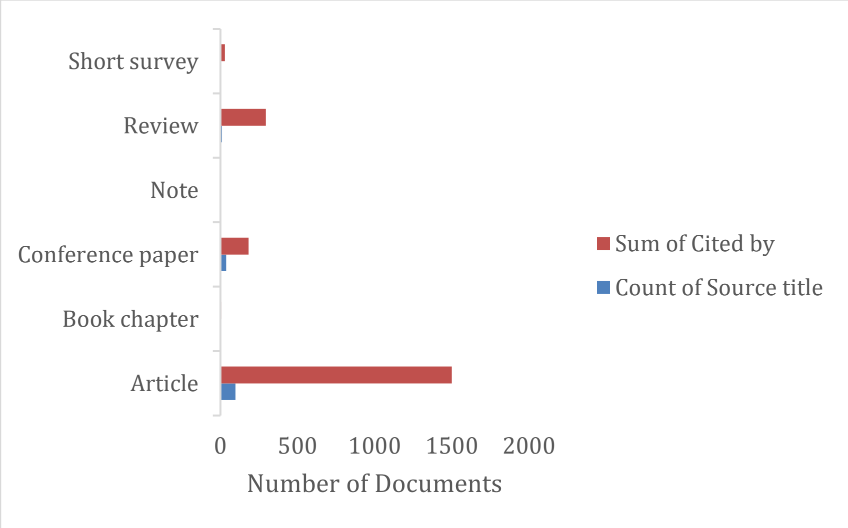

Figure 4: Count of Source Titles by Document and Citation

Table 1 and Figure 4 showcase the summaries of document type and their citations with articles recording 1500 citation, conference papers having 182, review articles 295, short surveys with 28, book chapters with 6 and Notes with 1 citation respectively.

3.2 Co-occurrence map based on country of authorship

This analysis aimed to classify the reviewed papers based on their geographic origin, revealing significant patterns in global contributions and collaboration. A map shown in Figure 4 was developed based on a criterion where a country must have a minimum of two documents and one citation to be considered. Hence, out of 40 countries, 23 met the threshold required. From the figure, as illustrated, China has the leading publication output, followed by the United States, India and Saudi Arabia. This shows the emphasis these countries put on research on AI, which is likely driven by their investments in advanced technological infrastructure, research funding and specialised institutions with specialised AI research programmes. The green and blue clusters in the map depict collaborations between China and the United States. While red clusters show the collaboration between India, Saudi Arabia and UAE, among others.

On the other hand, Pakistan, Egypt, Japan, Australia and the United Kingdom have smaller nodes, suggesting that the countries' emerging contribution and their interaction with leading countries highlight the interests in deep learning, offering new insights from various academic and industrial contexts. This network analysis focuses on the international efforts towards advancing deep learning methodologies, showcasing the relevance of global collaboration to foster innovation. Furthermore, it also highlights the geographical areas where research might be less active, suggesting potential opportunities for expanding deep learning and CAPP applications in underrepresented regions as depicted in Figure 5.

Received: 10-04-2025 / Accepted: 14-06-2025 / Published: 03-08-2025
https://doi.org/10.70118/ujet.2025.0202.26

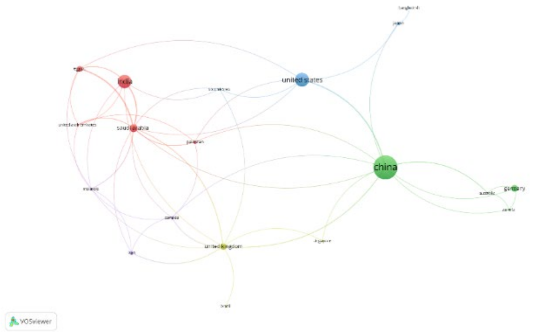

Figure 5: Co-occurrence map based on country of co-authorship

4.0 Computer-Aided Process Planning (CAPP)

CAPP serve as a bridge between design and manufacturing. It is a procedure of using computers for the selection of manufacturing processes and sequences of manufacturing operations, to achieve a desired product by the design specifications, at the right time and cost (Su, Chu, Chen, & Sun, 2015), (Xun, Lihui, & Newman, 2010). CAPP methodology has been used in the modification of traditional machining processes, It's the use of a computer system to automate the process of preparing detailed work and sequences of manufacturing a product. CAPP integrates several activities from machining feature recognition, selection of machining operation type, selection of manufacturing materials, setup planning and operation sequencing (Moghaddam, Soleymani,, & Farsi, 2015). There are basically two types of approaches to CAPP: - Generative and Variant CAPP.

Generative CAPP involves the generation of process plans using decision logic and process knowledge, which requires little human interference. It can effectively translate parts' geometrical (i.e. vertices, edges) information in CAD and CAM systems for process planning, derive a feasible process plan and grouping of machining operations, cost analysis, optimization of process plans, CNC code generation and feature pattern matching/recognition (Babic, Nesic, & Miljkovic, 2008). Generative CAPP is an intelligent approach of CAPP that generates process plans from geometry-based data, decision logic, algorithms and other factors that may influence production decisions, it is an essential linkage Computer Aided Design (CAD) and Computer Aided Manufacturing (CAM) to transform design data into manufacturing process with easier sequential operational procedures (Grabowik, Kalinowski, & Monica, 2005). Generative CAPP has its disadvantages because of its difficulty in obtaining features, representation, management, and human utilization in developing the desired output.

Variant CAPP on the other hand, adopts the use of similar stored parts in database to develop similar plans: - This method classifies similar parts into part families of similar manufacturing process using codes to enable easy identification (Leo & Zhang, 1989), (Xun, Lihui, & Newman, 2010) Variant CAPP depends on human intervention for classification, part information, data retrieval of similar process plans and making desired adjustments to produce output. The disadvantage of this process plan is that the successful implementation is based on the knowledge of the process planner.

2.1 Technologies for the Implementation of CAPP

Numerous technologies have been developed over the past few decades, including feature-based technologies, knowledge-based systems, neural networks, generic algorithms (GA), fuzzy set theory/logic, Petri net, STEP-compliant CAPP, among others (Xun, Lihui, & Newman, 2010).

2.2 Feature-based Technologies

Most CAPP systems function based on features or as a requirement for data input, which are basically achieved through feature extraction approaches; feature recognition and design by features (Xun, Lihui, & Newman, 2010).

Feature recognition examines the topological properties and geometrical dimensions of parts to identify the type of features. Feature-based recognition has several approaches; rule-based approach, volume decomposition, expert system and graph-based approach. Design-by-feature adopts a predefined feature stored in feature library to build parts with their geometrical dimension left at the discretion of the operator. Design-by feature approach has two methodologies which are destruction by machining features and synthesis by design features (Xun, Lihui, & Newman, 2010).

Research (Hyun Chan, Won Chul, & Hee-sok, 2007) has investigated the relation of features and their precedence in processing sequence, using projective feature recognition algorithm based on CAPP topographical sorting and breadth-first search of graphs from CAPP data. Feature-based generation of

Received: 10-04-2025 / Accepted: 14-06-2025 / Published: 03-08-2025
https://doi.org/10.70118/ujet.2025.0202.26

machining process plans for optimized parts manufacture (Mariusz & Mieczyslaw S., 2013) and it uses an approach of "branch and bound" a field of Artificial Intelligence to solve CAPP for manufacturing of systems in definite processing capabilities through identification of process alternatives and sequences for manufacturing.

Some works (Ahmad Faiz & Mohd Salman, Sub-delta volume generation for recognition of freeform cylindrical surface part model, 2018) investigated feature recognition in a case study of freeform cylindrical surfaces to minimize and optimize the material removal rate, cost of production of parts using sub-delta volume algorithm.

S.P Leo (S.P. Leo, Jerald, & S., 2014) attempted to develop a generalized process plan for the manufacture of micro parts using Automatic part-feature extraction using the feature-based model and knowledge-based system approach in the extraction of process planning activities and optimization.

Sanjit Moshat (Sanjit, Saurav, Asish, & Pradip, 2010) tries to elaborate the measures to inculcate quality and productivity through optimization of CNC end milling process parameters using PCA-based Taguchi method to provide good surface finishing and high material removal rate. Principal Component Analysis (PCA) was used to run the Taguchi analysis for the optimization and it was found to yield positive results in solving a multi-attribute decision-making problem.

Jian Gao (Jian, Detae, & Nabil, 2004) researched on the automatic generation of machining information from design system was very difficult to use in CAPP system due to differences in feature viewpoints and representation, the work addresses the difficulty in converting design feature representation into machining representation using mathematical model of feature mapping. The results showed that using Set Operation as the mathematical model was found to be effective in generating machining features.

Ahamad Faiz (Ahmad & Salman, 2016) researched to investigate the cylindrical axis detection and part model orientation for generating sub delta volume using feature based method to try and address the linkage between CAPP and CAD/CAM feature recognition of cylindrically oriented components to ensure adequate cutting parameters were set using feature based method approach and develop algorithm for generating sub delta volume for finishing (SDVF) and Sub delta volume for Roughing (SDVR) of the part model.

3.0 Deep Learning

Deep learning is a branch of Artificial Intelligence that focuses on investigating large data from either images, text, video or sound (Lee, Choiy, Choiy, Parkz, & Yoon, 2015), which is implemented using Neural Network Architecture, thus making deep learning an extension of neural network with several hidden layers (LeCun, Bottou, Bengio, & Haffner, 1998). Deep learning architectures comprise Deep Neural Networks (DNN), Convolutional Neural Networks and Recurrent Neural Networks (RNN) (Patel, Thakkar, Pandya, & Makwana, 2018).

This section focuses on the Convolutional Neural Network (CNN) architecture. The CNN enables the use of large and complex data distribution through the creation of parameters that increase the effectiveness of image classification (LeCun, Bengio, & Hinton, 2015). This further distinguishes deep learning from traditional machine learning processes as it adopts the use of integrated multiple layers that are data-driven, offers interaction between layers to enable effective learning (Hinton, et al., 2012) and reduces the need for computations of each layer (Xie, et al., 2019).

3.1 Convolutional Neural Networks

Recent breakthroughs in CNN have set the standard in image, video, and sound recognition using a system that mimics the human brain, structured in multiple layers for transformation of data (Wan, et al., 2014), (Anwar, et al., 2019). This branch of artificial neural network comprises several layers of learning, such as convolutional, sub-sampling, and fully connected layers, and in it, neurons serve as linkage between layers through weights and biases (Abiodun, et al., 2017), (Kattenborn, Leitloff, C., & Hinz, 2021). CNNs are derived from biologically inspired neurons with the ability to recognize visual patterns from image pixels using multiple-layer neutrons to prevent changes in scales, image distortions and shifts (Lee, Choiy, Choiy, Parkz, & Yoon, 2015) , (Kharazmi, Zheng, Lui, Wang, & Lee, 2018), (Anwar, et al., 2019).

CNN layers are arranged spatially in a grid structure with an inherent relationship between one layer to another, having a feature value built upon small spatial regions of the previous layer (Aloysius & Geetha, 2017), each layer in CNN comprises of 3-dimensional grid structure, which has a *height, width* and *depth* as shown in Figure 6. The first layer is the image with pixel size height*width, while depth stands for the colour channels (Long, Shelhamer, & Darrell, 2015). The parameter of the convolutional layer is a set of learnable kernels that convolve with feature maps to derive a separate 2-dimensional activation map that is aligned with the depth dimension to produce an output volume that reduces complexity in the input data (Abiodun, et al., 2017), (Aloysius & Geetha, 2017). The convolutional neural network functions like the feed-forward

Received: 10-04-2025 / Accepted: 14-06-2025 / Published: 03-08-2025

https://doi.org/10.70118/ujet.2025.0202.26

neural network with spatially organized connections between layers that perform convolution, pooling and Rectified linear unit (ReLU) (Aloysius & Geetha, 2017).

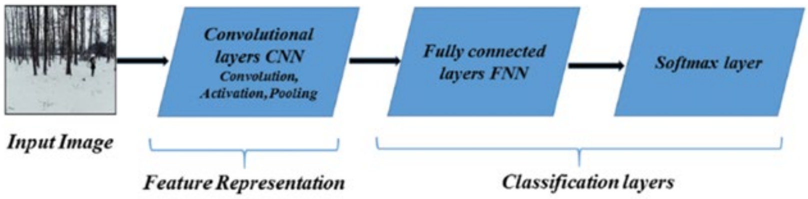

Figure 6: CNN structure (Tuama, Comby, & Chaumont, 2016; Athanasiadou, Geradts, & Eijk, 2018).

Convolution is essential in CNN; it comprises of mathematical operations (convolution) which perform feature extraction. The process of convolution adopts input as an array of numbers (kernels) across the output (output) tensor to derive an element-wise product between input and output, then adds them together to achieve an output value in the corresponding position of the output tensor called a feature map. The same sequence is repeated several times to form a greater number of feature maps with different characteristics. Convolution operations are mostly determined by the size and number of kernels. The sharing of weights by neurons reduces the complexity of the network and number of parameters (Yamashita, Nishio, Do, & Togashi, 2018), (Abiodun, et al., 2017), (Kattenborn, Leitloff, C., & Hinz, 2021), (Aloysius & Geetha, 2017). The purpose of this operation to sharing of weights of kernels across all image positions, which give rise to the following characteristics (Yamashita, Nishio, Do, & Togashi, 2018);

I. Kernels feature patterns extracted remain invariant as kernels travel across all image positions with the detection of learnable patterns,
II. Down-sampling in conjunction with a pooling operation,
III. Increasing model efficiency through reduction of learnable parameters.

Pooling layers are used to reduce the size of activation maps into smaller matrix without losing information, reducing number of parameters thereby reducing complications in computations (Wang, Zhao, & Pourpanah, 2020), widely used pooling operations includes; max pooling, average pooling, spectral, stochastic, spatial pyramid pooling and multi-scale orderless pooling (Gong, Wang, Guo, & Lazebnik, 2014; Nguyen, Yosinski, & Clune, 2015; Aloysius & Geetha, 2017). The most widely used pooling operation in CNN is the “max pooling”, this option extract patches from the input feature maps and return the maximum value in each patch as an output ignoring other values, has filter size of 2*2, stride (distance between two successive kernel positions) of 2 and an unchanged depth dimension of feature maps (Yamashita, Nishio, Do, & Togashi, 2018). Average pooling on the other hand deals with the arithmetic mean of the element in each of the pooling matrix. These operations have their own disadvantages as well, max pooling considers only the largest element in a feature map thereby ignoring other smaller elements in the pooling layer which could result in an abnormal output, meanwhile the average pooling will take the mean of all the elements in the feature map and if the elements are having smaller values, will further reduce the contrast of the new feature map drastically. However, a new proposed method has been developed which inculcate max and average pooling using a stochastic procedure when training CNNs, these procedures are termed Dropout and Drop-connect. Training CNN using Dropout enables the random selection that converts activation subsets to zero within each layer, while Drop-connect selects at random the subset of weights within the network to zero. The result of these procedures has proven to be more effective in regularization of CNNs (Yu, Wang, Chen, & Wei, 2014), (Wan, Zeiler, Zhang, LeCun, & Fergus, 2013), (Yamashita, Nishio, Do, & Togashi, 2018).

A fully connected layer is located after the convolutional and pooling layers, it is used in learning a summary of the data input representation. the layer identifies the output of the pooling layer into input, the features are identified and classified accordingly to the associated class (Athanasiadou, Geradts, & Eijk, 2018). It serves as a classifier (softmax) that addresses the discrepancy between desired and actual output with a multinominal logistic regression given out non-negative values with a normalized probability distribution over classes (Aloysius & Geetha, 2017), (Athanasiadou, Geradts, & Eijk, 2018).

3.2 Non-linear Activation functions

Activation functions plays a vital role in training of deep neural networks shown in Figure 7. The most common non-linear activation function used in CNN is the rectified linear unit (ReLU) it computes the function:

$$f(x) = \max(0, x) ----------(1)$$

Received: 10-04-2025 / Accepted: 14-06-2025 / Published: 03-08-2025

https://doi.org/10.70118/ujet.2025.0202.26

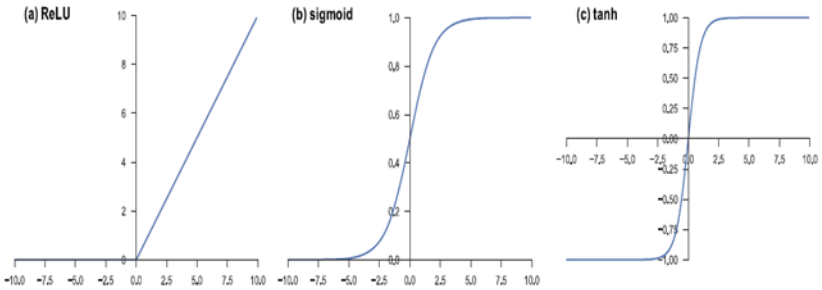

Figure 7: (a) Rectilinear Linear Function, (b) sigmoid function, (c) hyperbolic tangent (tanh) (Yamashita, Nishio, Do, & Togashi, 2018).

This function converts linear operations to non-linear for computation of output values of the layer (LeCun, Bengio, & Hinton, 2015; Athanasiadou, Geradts, & Eijk, 2018). ReLU function served as a milestone for effective training of supervised CNNs due to its simplicity and reliability in improving data across different models (Ramachandran, Zoph, & Le, 2017).

Other non-linear functions are sigmoid, hyperbolic tangent (tanh) (Yamashita, Nishio, Do, & Togashi, 2018):

Sigmoid function: converts a real-value function and output value in the range of 0 and 1into a non-linear value using

$$f(x) = \frac{1}{1 - e^{-x}} \quad ----------(2)$$

It has certain disadvantage; its outputs are non-zero centered which makes the gradient to oscillate between positive and negative values

Hyperbolic tangent (tanh): this is an improved version of the sigmoid function, it gives output values between -1 and 1, its outputs are zero centered, much preferred over the sigmoid function (Aloysius & Geetha, 2017).

$$\tanh(x) = 2f(2x) - 1 --------(3)$$

3.3 Dataset

There are several datasets used for image classification such includes ImageNet, MNIST, COCO, PASCAL, CIFAR and Open images (Yadav, Rathod, Pawar, Pawar, & More, 2021), (LeCun, Bottou, Bengio, & Haffner, 1998).

ImageNet is a hierarchy-organized image dataset that entails the collection of words or word sentences called "synset" or synonym collection with over 100000 synsets (Russakovsky, et al., 2015).

COCO is an object detection, segmentation and machine translation dataset specialized in large images >200k superpixel, it has 1.5 million items spread over eighty categories, five captions and over ninety object types, with wide functions as segmentation and context recognition it has a learning collection of defined images (Yadav, Rathod, Pawar, Pawar, & More, 2021), (Lin, et al., 2014).

CIFAR contains two datasets (CIFAR-10, CIFAR-100) the CIFAR-10 contains sixty thousand 32*32 color images, ten classes of six thousand each, it is further divided into training and testing images, six batches out of which five are for training and one is for testing of data. CIFAR-100 has twenty super classes divided into hundred classes with each having "fine" and "coarse" label (Yadav, Rathod, Pawar, Pawar, & More, 2021).

3.4 Implementation tools

DL architectures can be implemented using Java, C, C++, MATLAB and Octave extra, its algorithm libraries are Keras, Theano, Tensorflow among others are used to carryout mathematical computations of CNNs (Patel, Thakkar, Pandya, & Makwana, 2018), (Aloysius & Geetha, 2017).

3.5 Training of CNNs

Training of CNNs involves the adoption of backpropagation algorithm. There are basically three layers involved; convolution, ReLU, and pooling layers. Backpropagation in convolutional layer is a form of transposed convolution, it identifies kernels and weights of the fully connected layers which reduces the difference in output from the original dataset used for the training using a loss function through forward propagation. A loss function (cost function) measures the suitability of the expected output from the original dataset through forward propagation, loss functions are determined according to the specific process.

Gradient descent is an optimization algorithm that updates the weights and kernels to the negative direction of the gradient in order to minimize loss. The gradient is a partial derivative of the loss with respect to each learnable parameter (i.e. kernels, weights) given as:

Received: 10-04-2025 / Accepted: 14-06-2025 / Published: 03-08-2025
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$$\omega := \omega - \alpha * \frac{\delta L}{\delta w} - - - - - - - - - - - - - - - (4)$$

where ω = learnable parameter (i.e. kernels, weights), α = learning rate, L = loss function. The learning rate is the most important of the hyperparameters that must be set before a training can start it determines the size of the steps to take to reach minimum required point (Aghdam & Heravi, 2017), (LeCun, Bottou, Bengio, & Haffner, 1998), (Yamashita, Nishio, Do, & Togashi, 2018), (Ruder, 2017).

Gradient descent variants are of three major types which are determined by the amount of data used in computation, accuracy and time taken to perform an update. The variants are batch gradient descent, stochastic gradient descent (SGD), multi-batch gradient descent. Batch gradient descent (Vanilla gradient descent) allows one offline update at a time on a dataset, used for dataset that do not fit into memory, it converges for convex error surfaces. The SGD on the other hand, performs parameter update for large dataset in training, it allows more update and faster than Batch gradient descent with online data update, has high variance with complications of convergence of exact minimum due to overshooting, although when the learning is reduced gradually SGD tends to exhibit similar convergence as batch gradient descent for convex and non-convex optimizations (Ruder, 2017), (Phillips, 2021), (Pooja, Himanshu, & Jalal, 2020), (Pan, Niu, Li, Dou, & Jiang, 2019).

3.6 Applications of Deep Learning Methodologies

This section explores the diverse applications of DL methodologies in engineering practices and other related sectors, as illustrated in Table 2. The table categorises the applications of DL in computer-aided process planning, manufacturing systems and other allied industries such as healthcare.

Table 2:Deep Learning in Manufacturing Process

Themes	Authors	Focus
Deep learning in manufacturing systems	(Hua et al., 2024),(Hoffmann et al., 2025), (Huang et al., 2024), (Yan & Melkote, 2023a)	Emphasis on the use of machine intelligence to machining processes, adoption of deep learning for augmented process model dataset on manufacturing process models, use of data generation from CAD models to aid process planning, us of generative deep models to generate new designs without human intervention.
Medical applications of deep learning	(Moradi et al., 2025), (Wang et al., 2021), (AlGhamdi et al., 2023), (M.Fathalla et al., 2022),(Ramesh et al., 2023)	Emphasis on deep learning methodologies in high-dose rate (HDR) prostate cancer detection, Alzheimer disease, lung and colon cancer (LCC) diagnosis and pancreatic cancer (PC) detection performance to reduce human errors.

Highlights from Table 2. Showcases the studies that elaborated on the use of machine intelligence in manufacturing systems. Hua and his co-researchers (Hua et al., 2024) investigated the need for adopting machine intelligence in manufacturing processes with emphasis on machining processes to ensure timely production, cost-effectiveness of the products and improved quality and efficiency through the use of ML, knowledge graphs to build upon traditional computer-aided process planning. The study observed that the use of knowledge graph and deep reinforcement learning was able to achieve a unified representation and able to achieve a unified representation and reasoning, the use of historical processes and process rules, which in turn enhances the efficiency of the machining process design.

Deep learning adoption requirements of image datasets have led to its limited adoption in areas that require high knowledge to plan and process, to tackle this limitation. A process model augmentation with semi-supervised transfer learning to enlarge the existing dataset and train DL models effectively. The study experimented with the use of augmented process model datasets on manufacturing process models (Hoffmann et al., 2025). The effect of numerical control machining process planning, the study focuses on how data generated from CAD models can be used to generate a process scheme for a part with less time and lower cost (Yan & Melkote, 2023a).

Dubey (Dubey & Jain, 2019) conducted a survey on the use of face recognition technology capable of identifying an individual from images or video frames using deep learning methodology to properly identify, authenticate and access management to aid in investigation. Lee (Lee, Choiy, Choiy, Parkz, & Yoon, 2015) also adopted deep learning on radiographic image assessment in diagnosis of diseases, growth disorders using Finger Net based on CNN. The study showed 98% average detection accuracy.

Marcel (Marcel & Benedict, 2021) investigated the use of deep learning methodology (deep reinforcement learning) in production system as a review to showcase its applications and enable further research on

Received: 10-04-2025 / Accepted: 14-06-2025 / Published: 03-08-2025
https://doi.org/10.70118/ujet.2025.0202.26

shortening product development cycles and for customizable products. The study adopted a deep reinforcement learning to optimize throughputs, robustness and high adaptability or the production system, it further highlighted the application on variety of production systems because of its reduced need for human experience, flexibility and data-driven processes.

Other researchers conducted a review study on diagnostics segmentation techniques of cartilage and bone osteoarthritis research (Hong-Seng, Muhammad Hanif, Asnida, Yeng-Seng, & Akinobu, 2020) the review showed that deep learning could serve as reference for future computer-aided diagnosis applications and its advantages over magnetic resonance diagnosis. Xie (Xie, et al., 2019) identified that conventional approaches in diagnostics are slow, tedious and subjective to quality of the clinical imaging. As a result, the study adopted deep learning methodology (CNN) to achieve expert-level disease classification in many areas of diagnostics medicine that depends on image-base findings.

Akhter (Akhter, Jiangbin, Naqvi, Mohammed, & Muhammad, 2020) recognizes that machine learning has been used in text recognition but its use on Urdu text documentation classification is limited due to lack of language resources as such attempted to compare deep learning, machine learning models and other text pre-processing techniques. From the study, it was observed that convolutional neural networks performed better than other models.

Glaeser (Glaeser, et al., 2021) uses deep learning technology for fault detection in cold forging using vibration data to detect machine conditions resulting in defective products. CNN was used in performing detection and classification of faults. The result showed 92.66% accuracy of the process thus proving the potentials of CNN in detecting and classification of faults in manufacturing processes.

5.0 Future Directions

Today's manufacturing industries must adopt technological breakthroughs in order to meet a wide variety of consumer demands at the shortest possible time from production to supply. The global rise in population has rendered traditional manufacturing processes obsolete.

Artificial intelligence, through its branches, enabled the use of computers to effectively derive, create and modernise production processes to save time, cost and increase reliability. Process planning is an essential step in production, but it requires a highly skilled planner. However, with the advent of computers, the requirement for skilled planners has diminished in generating process planning for drawings, material selection, and manufacturing sequences for feature extraction. Artificial intelligence is making manufacturing smart through enhanced machine-to-machine communication, sensor networks, actuators, machine vision equipment, effective decision-making process. These advancements of Deep learning technologies their evolving and their applications are expanding across various fields, including the manufacturing sector and the health sector, where it is transforming manufacturing processes with high efficiency.

Convolutional neural networks are mostly used in image, video and sound recognition using systems that mimic the human brain with multiple layers for transforming data. Because of this feature, the CNN algorithm could be used in improving CAPP methodologies to increase efficiency in drafting a process plan for the manufacturing of machine parts.

DL technologies are utilised for various purposes in manufacturing, such as parts machining, process planning, computer-aided design automation and many more. These advances are transforming the manufacturing world with improved processes and increased efficiency in the production of goods and services (Ning et al., 2023; Riesener et al., 2024; Vatandoust et al., 2025; Yan & Melkote, 2023b).

Another aspect is in their application in the health sector, where it is used in disease diagnosis and treatment planning of several health problems, such as Lung and colon cancer (LCC), prostate and pancreatic cancer. Computed Tomography (CT) scans are utilised through DL methodologies to increase production and treatment efficiency in patients and reduce human errors in treatment (AlGhamdi et al., 2023; Carcagnì et al., 2023; Hussong et al., 2023; M.Fathalla et al., 2022; Moradi et al., 2025; Ramesh et al., 2023; Sadr et al., 2025; Shen et al., 2023; Singh & Agarwal, 2023).

The presented approaches have demonstrated the capabilities of deep learning and computer-aided process planning. The study showcases the various applications and areas of future research that will serve as a basis for understanding DL and CAPP subsequently their integration into feature recognition for NC machine applications through algorithms development and implementation.

6.0 Conclusions

Process planning is the linkage between design and manufacturing. It describes the manufacturing process, sequences, and material selection to transform design into a physical product at a cost-effective rate, with precision and accuracy to design specifications and faster production time to meet the required demand. Before the use of computers in process planning, traditional process planning required skilled and experienced manufacturing planners, which made the process slow and unfriendly for younger operators.

Received: 10-04-2025 / Accepted: 14-06-2025 / Published: 03-08-2025

https://doi.org/10.70118/ujet.2025.0202.26

With the increasing demand and unpredictable market forces for complicated products by consumers, manufacturing has adopted the use of computers to aid in process planning. This new route optimises the traditional process with the aid of computers, which integrate computer-aided design and computer-aided manufacturing to boost production and ease the dependence on traditional process planning methodologies. But the challenges of recognising component features are still being researched using different approaches. Features are essential attributes of a component that distinguish each product.

This review paper presents a review of the existing methodologies in feature extraction through computer-aided process planning and also highlights the potential of convolutional neural networks. The paper pointed to the fact that with its application over diverse fields, CNN can be used in feature recognition and extraction through classification of various parts in manufacturing to enhance the computer-aided decision-making process for efficient process planning.

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Received: 10-04-2025 / Accepted: 14-06-2025 / Published: 03-08-2025

https://doi.org/10.70118/ujet.2025.0202.26