10.48047/jocaaa.2024.33.06.51

A Review of Intelligent Process Planning of Prismatic Components using AI and IoT in CNC Milling

Ms. Neha Chauhan
Assistant Professor, Department of Mechanical Engineering, Dronacharya College of Engineering, Gurugram, Haryana
neha.chauhan@ggnindia.dronacharya.info

Dr. Shailesh Singh
Associate Professor, Department of Mechanical Engineering, Dronacharya Group of Institutions, Greater Noida, Uttar Pradesh
shailesh.singh@gnindia.dronacharya.info

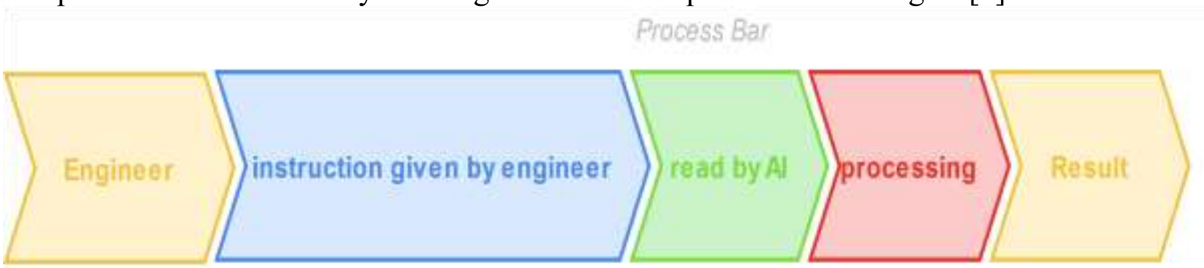
Abstract

Computer-aided process planning (CAPP) systems help human planners create better process strategies to address the challenges of manual process planning. Manual process planning requires knowledge in documentation, tool selection, machine selection, cutting parameters selection, and decision-making. CAPP bridges the gap between computer aided design and manufacturing, using new artificial intelligence techniques. Feature-based modeling is used in CAPP, with SolidWorks software used for CAD modeling and storing part manufacturing details in STEP 242 file format. Artificial neural network techniques (ANN) are applied for machining operation selection and cutting tool selection, considering various prismatic features. The generated NC codes are monitored using Internet of Things concepts, such as sending data from a Particle Photon device connected to a CNC milling machine to ThingSpeak. This research reduces process planning time for complex prismatic components, resulting in a significant reduction in overall manufacturing lead time.

Keywords: CAPP, CAD, ANN, CNC, Intelligent Process

Introduction

Computer-Aided Process Planning (CAPP) is a tool that helps bridge the gap between design and manufacturing by assisting human planners in producing better process plans [1]. CAPP systems use various approaches, such as variant, generative, and semi-generative methods. Modern CAPP approaches include feature-based techniques, knowledge-based systems, genetic algorithms, fuzzy logic methods, Petri nets, agent-based technology, and the Standard for Exchange of Product Data (STEP). Artificial neural networks are used for rotational components and less for prismatic components, with research focusing on SolidWorks STEP feature-based modeling for machining features and interfaces with neural networks for process planning. IoT-based CNC machine monitoring is also being explored, utilizing IoT principles to monitor CNC cutting tool status. Overall, CAPP helps reduce process planning and production lead times by utilizing various techniques and technologies [2].



10.48047/jocaaa.2024.33.06.51

Fig.1 Define how AI makes work easy in Mechanical Engineering

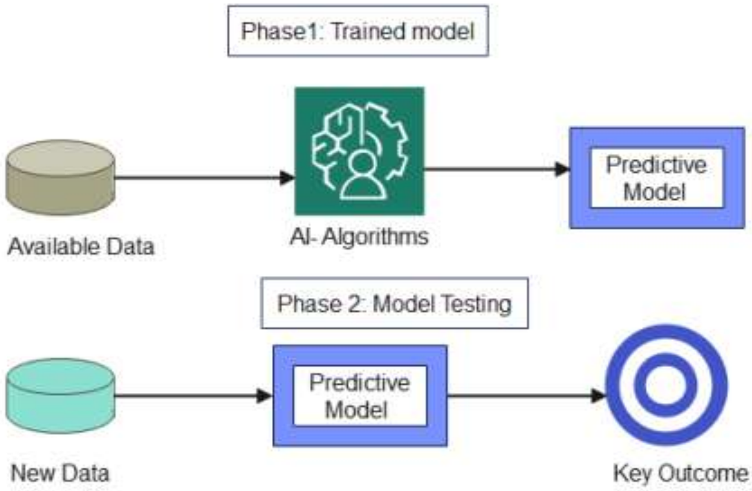


Fig. 2 A General Framework of AI-Based Predictive Mode

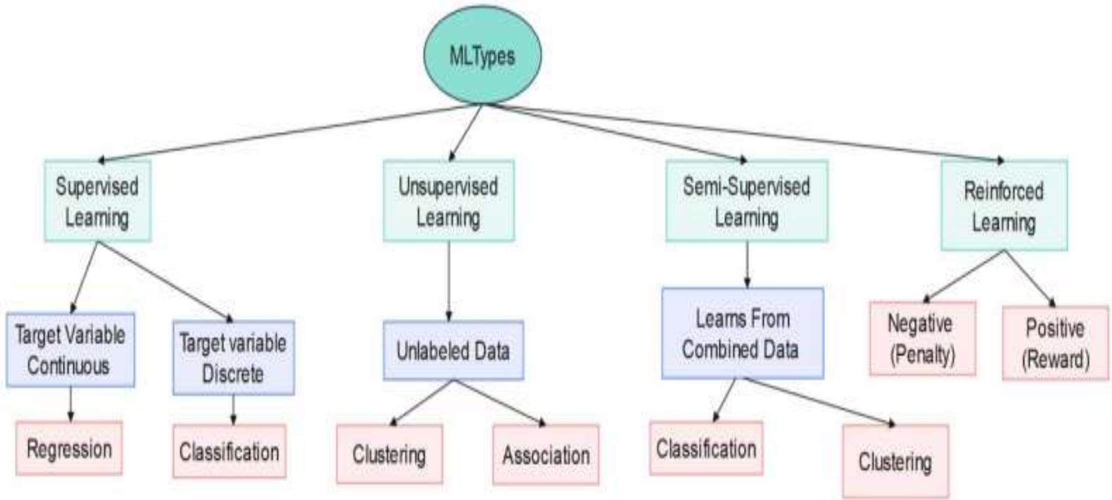
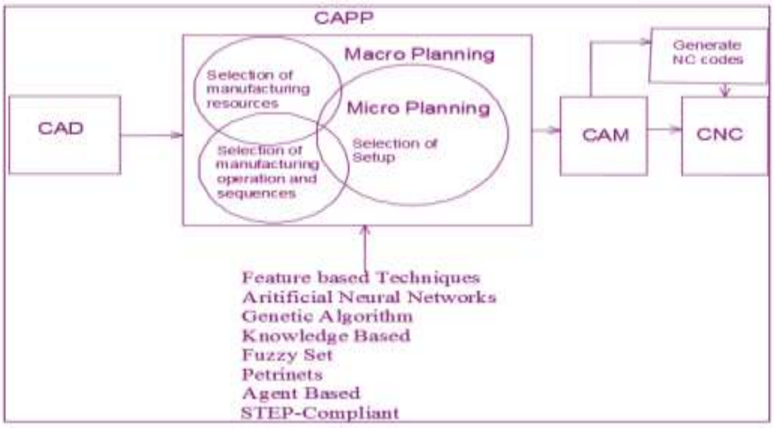


Fig. 3 Different Learning Schemes

10.48047/jocaaa.2024.33.06.51



:

Fig. 4 CAPP approaches

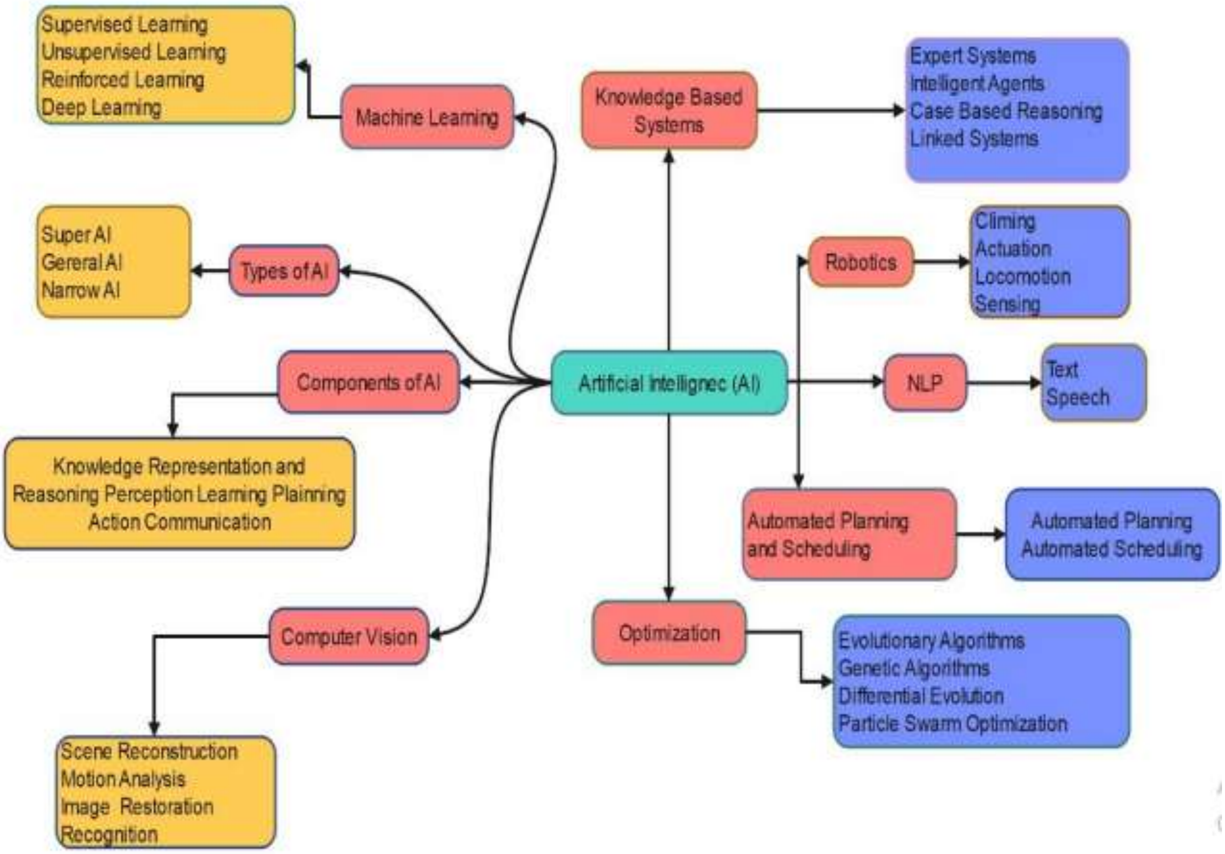


Fig.5 AI and its subfield

This research investigates computer-aided process planning (CAPP) and automates activities such as neural network-based machining operation selection and cutting tool selection. Neural networks are used for machining operations and cutting tools, with the Levenberg Marquardt algorithm being the most effective method [3]. Setup sequencing, cutting

10.48047/jocaaa.2024.33.06.51

parameters selection, and NC code generation are performed using SolidWorks software, which provides instructions for machining parts in a specific sequence based on priority rules [4].

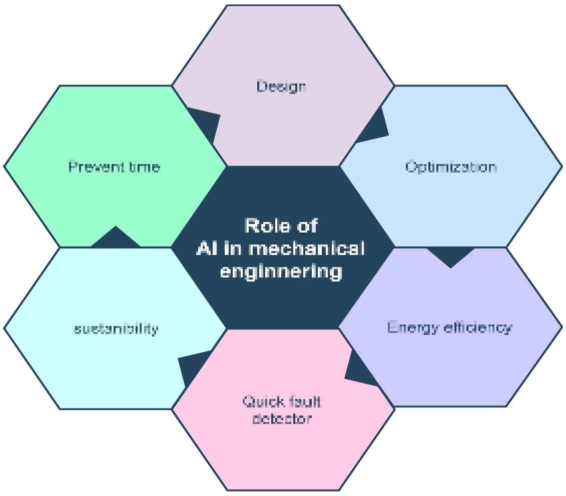


Fig. 6 Role of AI in Mechanical Engineering

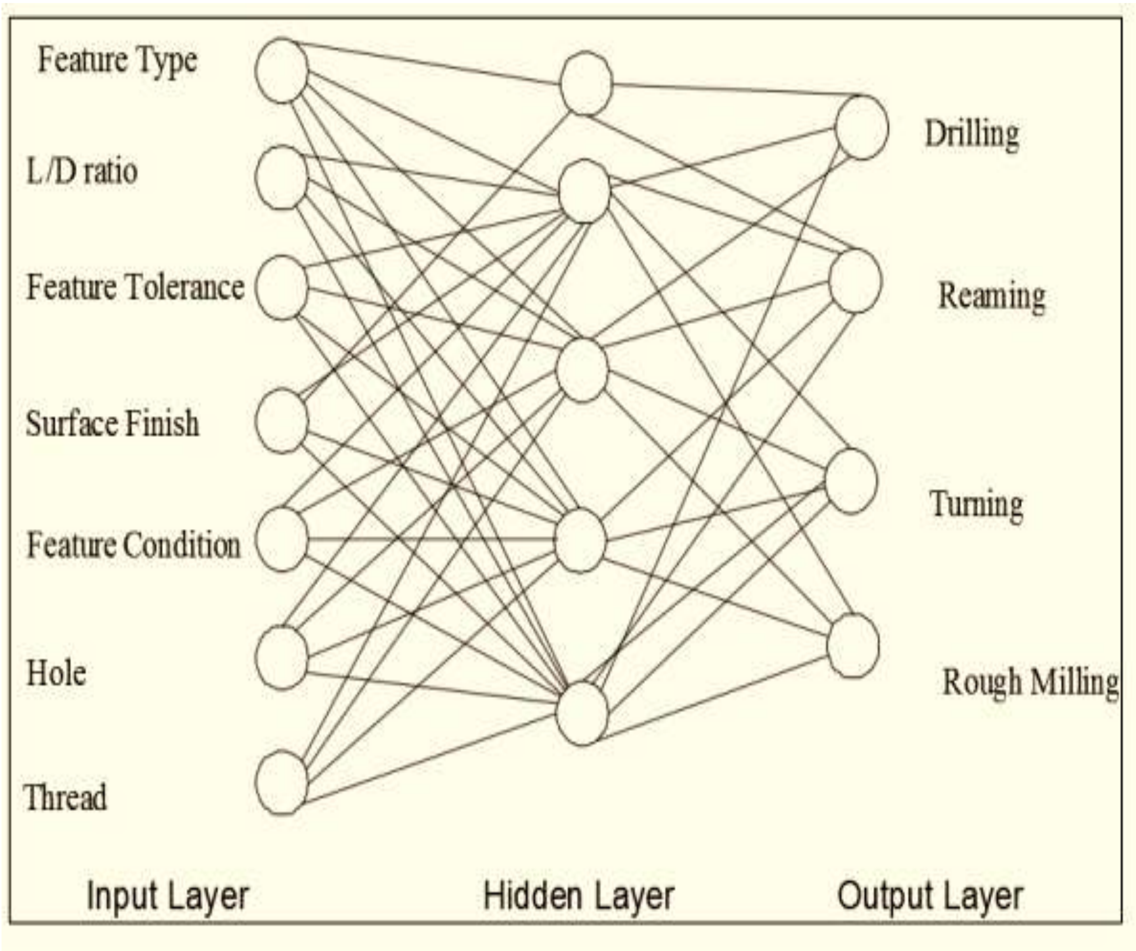


Fig. 7 ANN for the operation selection

10.48047/jocaaa.2024.33.06.51

The NC program consists of tool path and machine tool operating commands. The SolidWorks CAM technology database, Tech DBTM, is a self-populating database that can be customized to meet user and shop floor requirements [5].

Internet of Things (IoT) is also used for CNC machine monitoring, with instructions on sending data (cutting tool status-time) from Particle Photon to open-source software ThingSpeak. The Particle Photon device and infrared sensor device are connected to the CNC milling machine, and the cutting tool status is monitored using infrared technology. The research aims to reduce machining time by 60% for complex prismatic components, with major contributions including STEP feature-based modelling of the prismatic components [6].

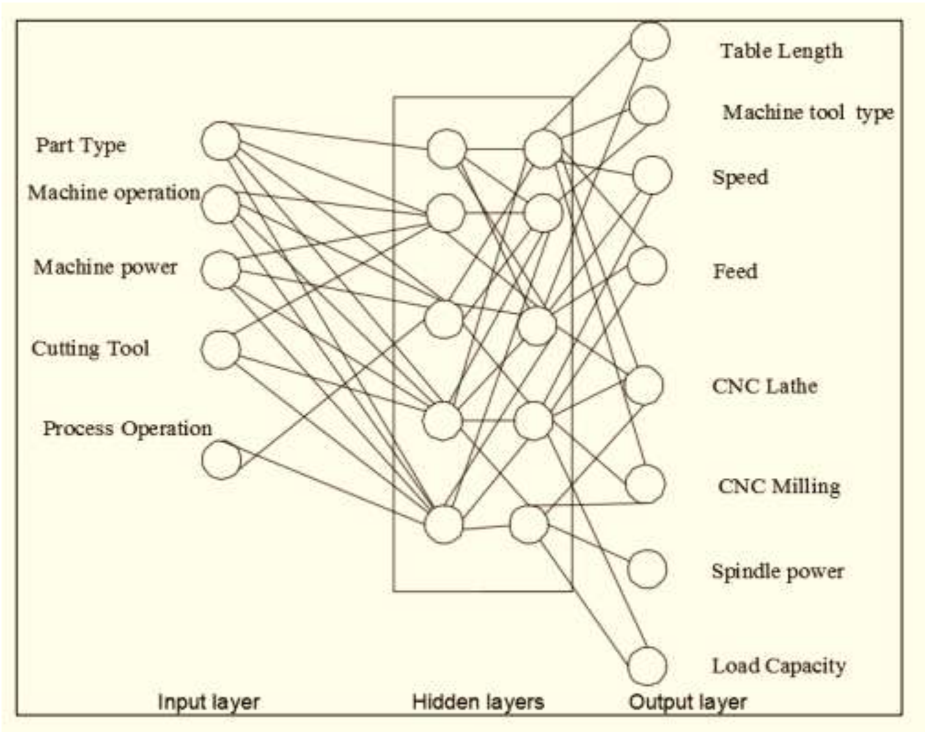
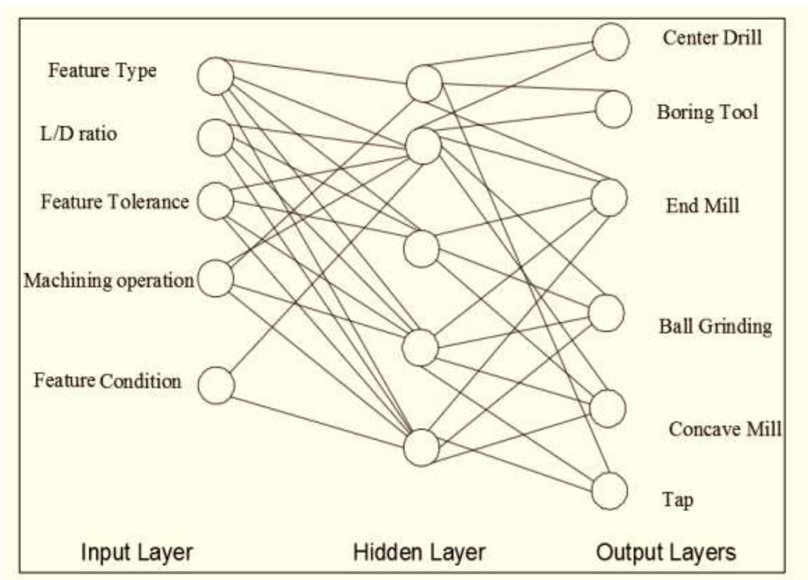


Fig. 8 ANN for the machine tool selection



10.48047/jocaaa.2024.33.06.51

Fig. 9 ANN for the cutting tool selection

Methodology and Result Analysis

This paper focuses on the application of artificial neural network (ANN) techniques in Computer-Aided Manufacturing (CAPP) due to their learning ability and potential for dynamic planning [7]. ANN plays a vital role in feature recognition, machine selection, operation selection, and cutting tool selection. Literature surveys in feature-based modeling and Internet of Things in machining and manufacturing are also covered in detail [8]. Various ANN techniques have been proposed for feature recognition, machine selection, operation selection, and cutting tool selection. Some researchers use image data as input for training, while others use a B-Rep solid modeler database for feature recognition. Other researchers propose a cascaded structure backpropagation type neural network for 3D block-shaped components, and an artificial intelligence-based neural network for dealing with arbitrary features [9]. CAPP hybrid algorithm integration has been proposed by Mei et al. for datum selection using the backpropagation algorithm, Santochi et al. for cutting tool selection, and Joo et al. for operation selection and sequencing. A new concept called feature-based modeling (FBM) is developed to represent design because of manufacture. Ming et al. use a hybrid neural network (genetic algorithm and ANN) for optimal solution, producing the best results compared to other approaches like the Hopified neural network approach and hybrid simulated annealing- Hopified network approach [10]. ANN plays a vital role in pattern recognition, and feature-based approaches are essential tools for integrating CAD with CAPP. Many feature recognition systems, such as graph-based, volume decomposition-based, syntactic pattern recognition, and hybrid approaches, are used in process planning. ANN feature recognition can learn feature patterns and tolerate noise in an input pattern. In conclusion, ANN plays a vital role in feature recognition, machine selection, operation selection, and cutting tool selection in CAPP [11].

10.48047/jocaaa.2024.33.06.51

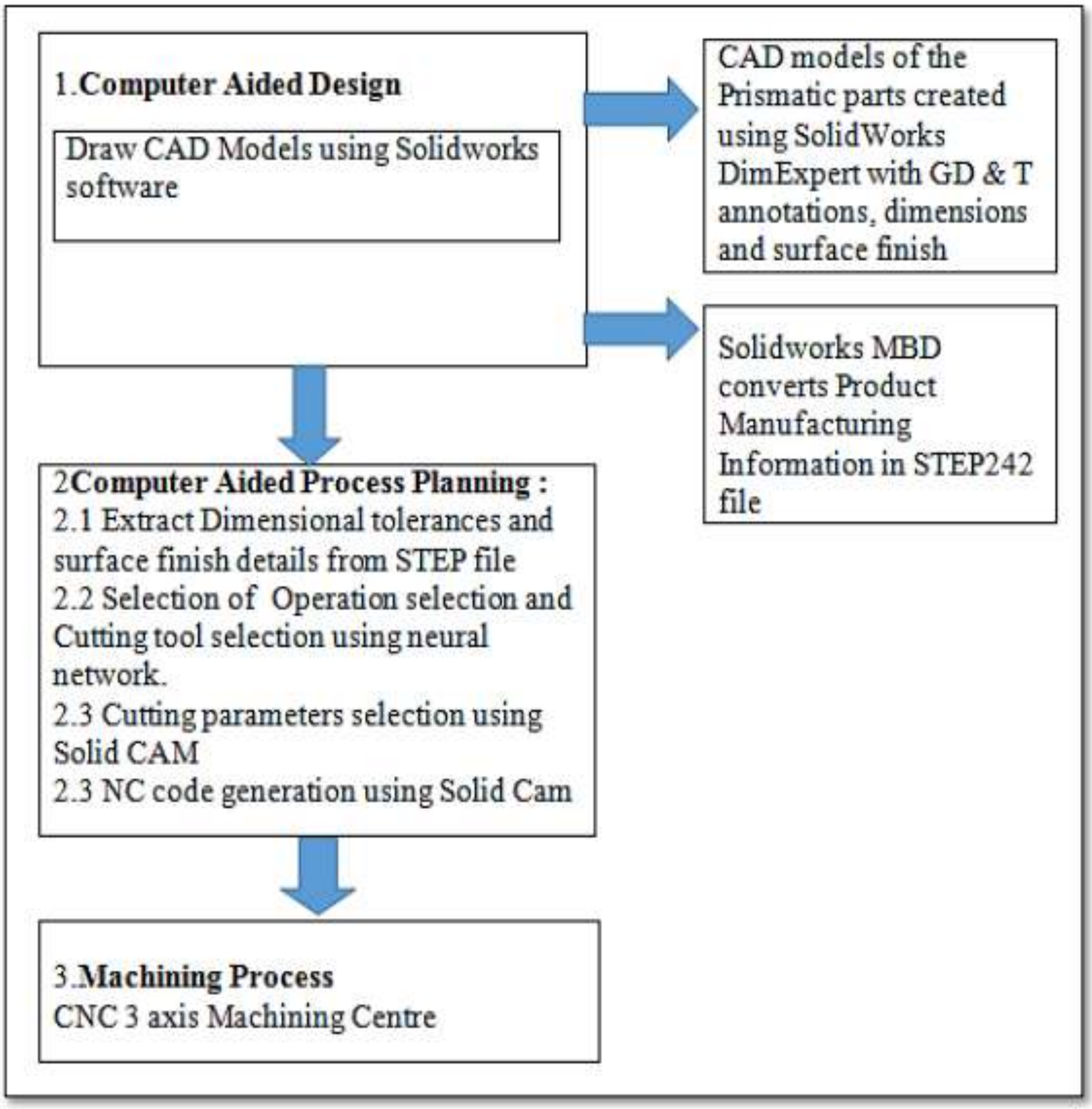


Fig. 10 Major steps analysis

Table 1 Results obtained using three networks (Linear, MLP, and RBF)

Network	Linear	MLP	RBF
Learning quality	0.975	0.732	0.6959
Test quality	0.997747	0.72525	0.6216
Learning error	0.2308	0.1629	1.179
Testing error	0.237306	0.164	1.3326

10.48047/jocaaa.2024.33.06.51

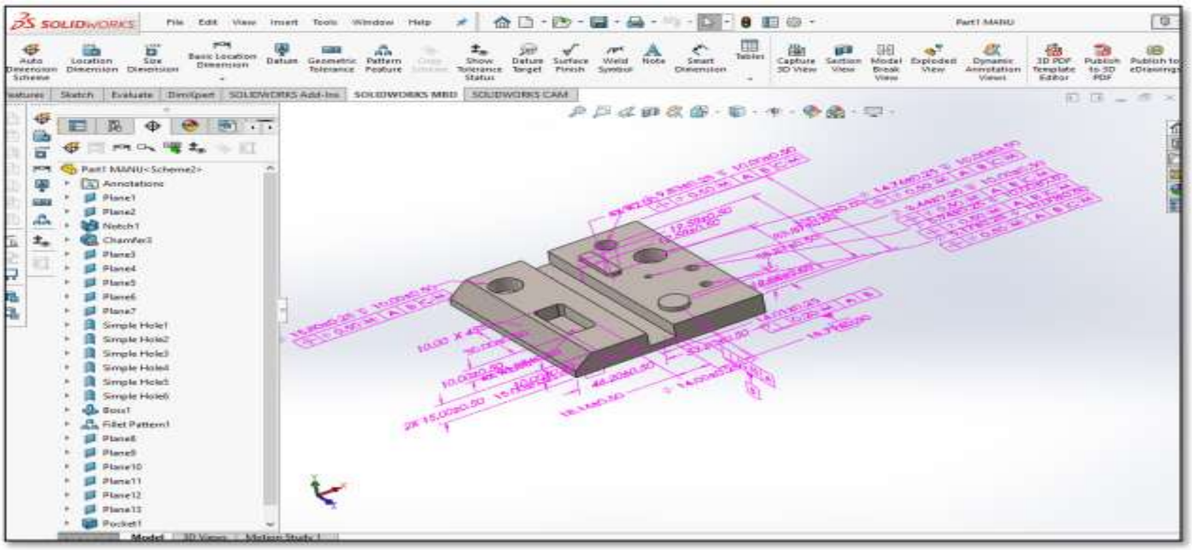


Fig. 11 Analysis report-1

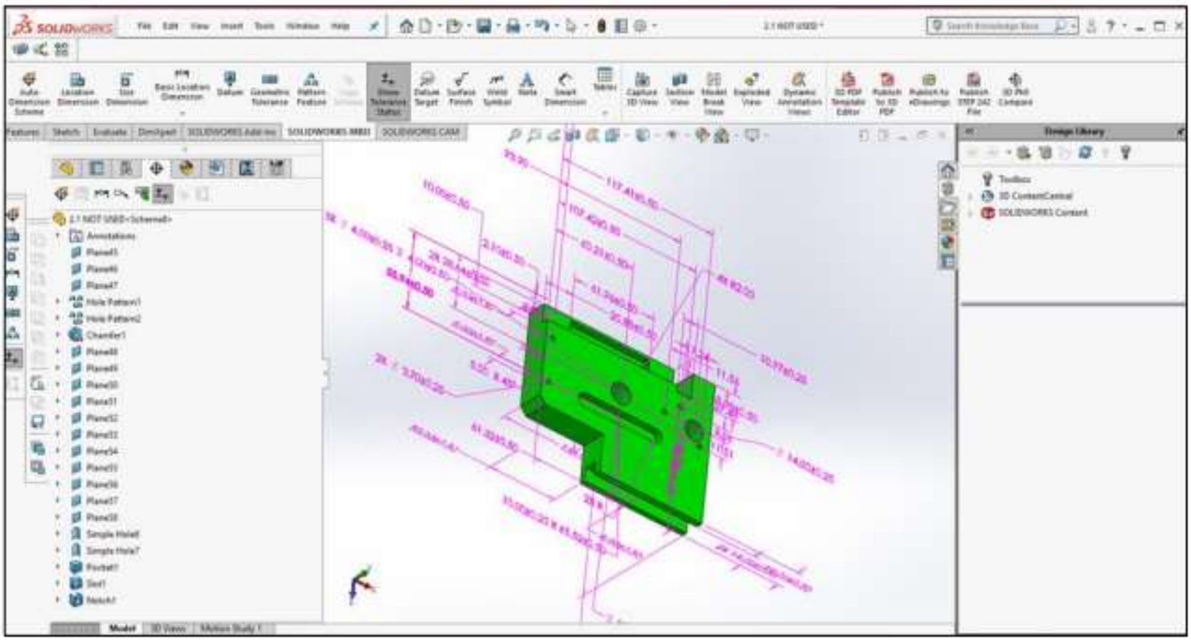


Fig. 12 Analysis report-2

10.48047/jocaaa.2024.33.06.51

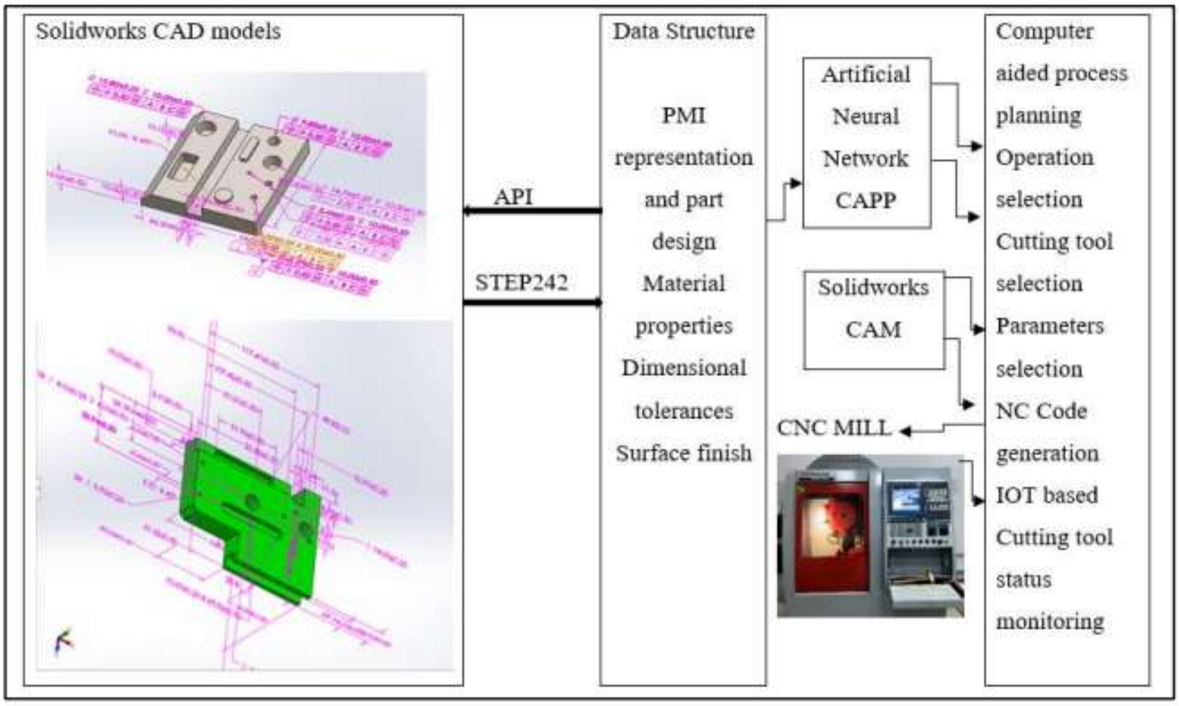


Fig. 13 CAD/CAPP integration

This research paper discusses feature-based modeling for prismatic components using SolidWorks 2018 software [12]. The software is used for CAD modeling and storing part manufacturing details in STEP 242 file format. The intelligent CAPP system generates the best machining operations for prismatic components based on tolerances, material requirements, and surface finish. Techniques such as feature-related, knowledge-based, artificial neural networks, genetic algorithms, fuzzy logic, Petri networks, web-based technology, and STEP databases techniques are used. The paper also discusses parametric part modeling in SolidWorks, which involves creating a sketch with dimensions, implementing geometric relationships, protruding, rotating, or sweeping the sketch to create a solid model, modifying the model as needed for analysis, and creating necessary drawing views to document the template [13]. A comprehensive Computer-Aided Process Planning (CAPP) system involves steps such as recognizing part features, machining process determination, sequencing, machine and tool selection, material selection, machining parameters selection, and preparing process plans. Feature technology is an important CIM tool in the manufacturing sector, as it allows computers to assess the database for process plans freely. Intelligent process planning (ST-CAPP) is deployed to integrate process planning and use STEP-NC standards that transform design entities to manufacture features. Automatic recognition of features is an essential module in knowledge-based machining for analyzing a model, identifying various features, and extracting features for downstream applications. SolidWorks2018 is used for solid 3D modeling, primarily for various prismatic features [14]. DimXpert is used to create product data information, which is automatically extracted after filtering tolerance type, datum, surface finish, and different features. This information is provided as input in decision-making and process planning [15]. The Standard for the Exchange of Product Model Data (STEP) files play a crucial role in sharing process plan information to downstream applications. The latest version of the STEP protocol, AP242, is strongly recommended for CAPP systems [16-19]. The STEP file comprises

10.48047/jocaaa.2024.33.06.51

dimension details, tolerances, material information, and surface finish details, which are interfaced with an artificial neural network for machining operation selection and cutting tool selection [20].

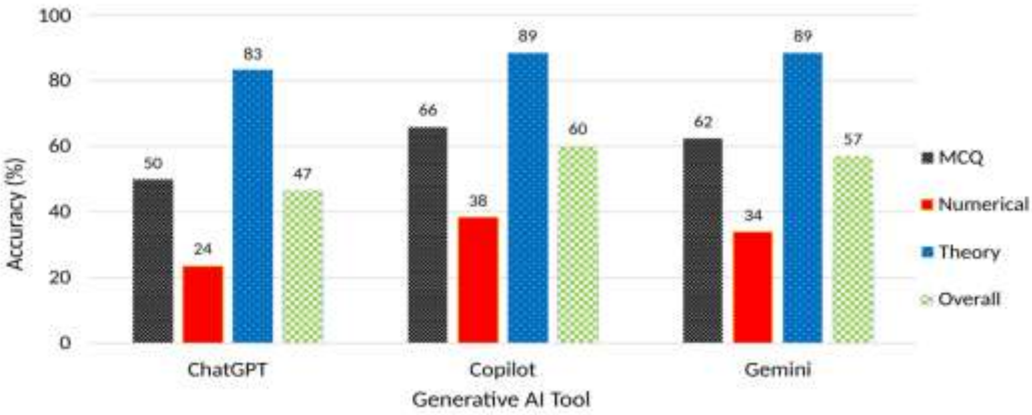


Fig.14 Analysis report

Conclusion

Computer-aided process planning systems (CAPP) are used to assist human planners in producing better process plans. These systems involve feature-based modeling for prismatic components, artificial neural network-based machining operation and cutting tool selection, setup sequencing, cutting parameters selection, and numerical code generation. The intelligent CAPP system suggests the best machining operation and its sequences for prismatic components using tolerances, material requirements, and surface finish details. The Levenberg Marquardt algorithm is used to train the networks, and Matlab 2018 software is used for training. The proposed CAPP reduces process planning time by over 60% for complex prismatic components, reducing overall manufacturing lead time. The use of the STEP methodology helps integrate the CAD system with the developed CAPP system. The research is highly recommended for small-scale industries manufacturing prismatic components using three-axis CNC milling machines. Future work will focus on the application of neural networks in selecting more machining features, 3D convolution neural network for feature recognition, and extending the use of artificial neural networks to cutting parameter selection, setup sequencing, and NC code generation in process planning.

Reference:

1. Abasolo, J. M., & Gomez, M. (2000). MELISA: An ontology-based agent for information retrieval in medicine. Proceedings of the 1st international workshop on the semantic web (SemWeb2000), 73–82.
2. M. Z. Hossain, F. Uz Zaman and M. R. Islam, "Advancing AI-Generated Image Detection: Enhanced Accuracy through CNN and Vision Transformer Models with Explainable AI Insights," *2023 26th International Conference on Computer and Information Technology (ICCIT)*, Cox's Bazar, Bangladesh, 2023, pp. 1-6, doi: 10.1109/ICCIT60459.2023.10440990.
3. I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in *Advances in Neural Information Processing*

10.48047/jocaaa.2024.33.06.51

Systems (Z. Ghahramani, M. Welling, C. Cortes, N. Lawrence, and K. Weinberger, eds.), vol. 27, Curran Associates, Inc., 2014.

4. Abdel-Karim, B. M., Pfeuffer, N., & Hinz, O. (2021). Machine learn ing in information systems - a bibliographic review and open research issues. Electronic Markets, 31(3), 643–670. https:// doi.org/10.1007/s12525-021-00459-2
5. G. D. Vynck, "Ai images are getting harder to spot. google thinks it has a solution.," *The Washington Post*, 2023. Accessed on September 14, 2023.
6. Ågerfalk, P. J. (2020). Artificial intelligence as digital agency. Euro pean Journal of Information Systems, 29(1), 1–8. https:// doi. org/10.1080/0960085X.2020.1721947
7. A. Ramesh, P. Dhariwal, A. Nichol, C. Chu, and M. Chen, "*Hierarchical text-conditional image generation with clip latents*," 2022.
8. Alt, R. (2018). Electronic markets and current general research. Electronic Markets, 28(2), 123–128. https:// doi. org/ 10. 1007/ s12525-018-0299-0
9. Alt, R. (2021). Electronic markets on the next convergence. Electronic Markets, 31(1), 1–9. https:// doi. org/ 10. 1007/ s12525-021-00471-6
10. Arnott, D. (2006). Cognitive biases and decision support systems development: a design science approach. Information Systems Journal, 16(1), 55–78. https:// doi. org/ 10. 1111/j. 1365- 2575. 2006.00208.x
11. 'The role of generative AI tools in shaping mechanical engineering education from an undergraduate perspective.' By Harshal Akolekar https://www.nature.com/articles/s41598-025-93871-z
12. 'Applications of Artificial Intelligence in Mechanical Engineering' by Ferit Artkin

    https://dergipark.org.tr/en/download/article-file/2851620

13. S. Shaffi, "'it's the opposite of art': why illustrators are furious about ai," *The Guardian*, 2023. Accessed on September 14, 2023.
14. H. Zhao, W. Zhou, D. Chen, T. Wei, W. Zhang, and N. Yu, "*Multi-attentional deepfake detection*," 2021.
15. A. Dosovitskiy, L. Beyer, A. Kolesnikov, D. Weissenborn, X. Zhai, T. Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, and N. Houlsby, "*An image is worth 16x16 words: Transformers for image recognition at scale*," 2021.
16. . J. Bird and A. Lotfi, "*Cifake: Image classification and explainable identification of ai-generated synthetic images*," 2023.
17. S. Paul and P.-Y. Chen, "*Vision transformers are robust learners*," 2021.
18. K. Roose, "An AI-generated picture won an art prize. Artists aren't happy," *New York Times*, vol. 2, p. 2022, Sep. 2022.
19. R. Rombach, A. Blattmann, D. Lorenz, P. Esser, and B. Ommer, "High-resolution image synthesis with latent diffusion models," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2022, pp. 10684–10695.
20. N. Bonettini, P. Bestagini, S. Milani, and S. Tubaro, "On the use of Benford's law to detect GAN-generated images," in *Proc. 25th Int. Conf. Pattern Recognit. (ICPR)*, Jan. 2021, pp. 5495–5502.