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# Machining Cost Estimation using AI

Rutwik Ingale<sup>1</sup>, Anirudha Karande<sup>2</sup>, Swarali Gulwade<sup>3</sup>, Pratik Patil<sup>4</sup>

Dr. Sachin Jambhale<sup>5</sup>

U.G. Student, Department of Mechanical Engineering, D. Y. Patil College of Engineering, Akurdi, India<sup>1-4</sup>

Asst. Professor, Department of Mechanical Engineering, D. Y. Patil College of Engineering, Akurdi, India<sup>5</sup>

**ABSTRACT:**The suggested strategy is based on creating an automated model of intersecting machining feature recognition system for cost estimation, which can boost the business' productivity by generating quotes in a matter of seconds, and that manufacturers identify and eliminate cost drivers early in the life cycle, before an error is compounded with additional layers of design detail that are expensive to unwind. As product development and quoting cycles increase shorter, more businesses are using improved cost estimation abilities to pursue lean manufacturing and other cost-saving strategies. A company won't be able to effectively compete in the global market if they don't apply these strategies. This relentless quest of cost optimization has been made possible by the arrival of new technology that enables these creative cost-cutting tactics.

**KEYWORDS:**Cost estimation, mass production, mechanical part processing, deep learning, Convolutional Neural Network, Single Shot Multibox Detector (SSD), 3D feature localization, accuracy, manufacturing costs, productivity.

## I. INTRODUCTION

In the context of mass manufacturing based on bespoke designs, it is critical to estimate the cost of the parts fast and precisely. Mechanical component processing businesses have long been concerned with responding to client questions in order to compete in a competitive environment. To accomplish so, they must assure a reasonably low product cost. Though component design accounts for just approximately 5% of total product development costs, it determines 70% to 80% of mechanical part costs. The product's design may thus be optimised if the cost of the pieces is precisely calculated throughout the design stage. Estimated costs are numerical estimates of the resources needed to process components. A cost estimation, as opposed to a cost calculation, A cost estimation is based on the assumption that the firm does not have access to a production schedule or manufacturing process data. It is broken down into direct and indirect charges. Direct costs are the costs of manufacturing components such as design, material, and processing. Indirect costs are costs related to a product that cannot be immediately identified. These expenses include the factory lease, the depreciation rate on equipment, and sales and administrative expenses. An estimation of costs is a typical mathematical regression issue, which entails developing a sophisticated model of the complex relationships in the sample in order to forecast occurrences. Therefore, the motivation for our study is to develop an AI model (a Deep learning based Convolutional Neural Network based model) to quickly estimate manufacturing costs to **increase company's productivity.**

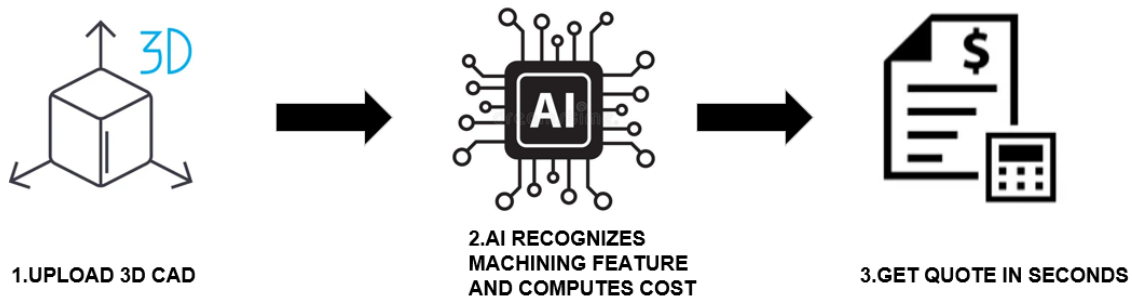


Figure 1 General layout of working of project

## II. LITERATURE SURVEY

1. Fangwei Ning et al.: In this research study, the author talked about estimating manufacturing costs using deep learning. It is common practise to build a regression link between the two costs using cost estimating methods that are based on the processing elements of the component's features and cost. In order to identify processing attributes and calculate the cost of parts, we have employed deep-learning algorithms that have the capacity to automatically discover complicated high-level data features from large amounts of data. To develop an incredibly accurate feature recognition method, this research first proposes a ground-breaking three-dimensional (3D) convolutional neural network (CNN) component.

2. Soyoung Yoo et al.: In this paper, an explainable artificial intelligence-based manufacturing cost prediction method for 3D computer-aided design (CAD) models is proposed. With the suggested method, it is feasible for us to comprehend how the 3D CAD model's machining features affect the rise in manufacturing expenses. The three steps that make up the suggested technique were used by us: collecting and prepping data, researching 3D deep learning architecture, and visualising the predictions' outcomes. The proposed deep learning approach exhibits good manufacturing cost predictability for CNC-machined components. especially when 3D gradient-weighted class activation mapping is employed Early in the design concept process, we might provide engineering designers with design guidance utilising the suggested technique to help them reduce manufacturing costs.

3. Siu L. Chan, Yanglong Lu et al.: In this research study, the seamless integration of manufacturing-related hardware and software tools is made feasible via a novel paradigm called as "cybermanufacturing." These materials are offered as services online. This paradigm promotes tool sharing and reuse, which can speed up product development and save costs. As a consequence of research, a novel framework for cost estimation built on big data analytics technologies has been created in order to forecast the manufacturing costs related to a new job based on costs connected with previous jobs that are comparable to it.

4. Alqahtani, A. Whyte et al.: In this research, the author talked about how artificial neural networks may be used to incorporate cost-relevant items into estimations that will improve life-cycle costing for building projects. In the era of mass customisation, a product's competitiveness can be increased by a rapid and precise assessment of the production costs of various components. The manufacturing sector's complex mapping linkages are challenging to construct using the regression-model cost estimate approach because of the components' dynamic roles, detailed structure, and very complex processing connections. The study explores deep learning techniques, a relatively new field of technology that can automatically comprehend intricate mapping relationships and high level data attributes from a vast quantity of data.

5. T.M.S. Elhag et al.: This paper's recommendation of a feature-based method to cost prediction for machined components is its main objective. Cost estimation must be quick and precise since it gives designers essential information. Four groups of manufacturing aspects are identified in this study. Manufacturing operations are the starting point for cost analyses for all category features. The early cost predictions were inaccurate because manufacturing activity was not taken into account. Cost is inversely related to machining time, which includes both active and passive time. Rough cutting time and final cutting time are both included in operational time. In this article, a cost estimation technique based on manufacturing attributes was created. The technology created via research may be employed in a design department to get accurate cost data at an early stage.

6. Peizhi Shi et al.: In Industrie 4.0, machines are expected to be autonomous, self-aware, and self-correcting. A crucial aspect in manufacturing is feature recognition, which involves detecting machining features from a 3D model. However, accurately recognizing and locating intersecting features poses a significant challenge due to damaged topology information. To address this problem, a deep learning approach called SsdNet is introduced, inspired by the single-shot multibox detector (SSD). Unlike the original SSD designed for 2D object detection, SsdNet is tailored for 3D feature recognition. The network architecture and output of SSD are modified accordingly, and advanced techniques are incorporated to enhance recognition performance. Experimental results on a benchmark dataset demonstrate that the proposed method achieves state-of-the-art feature recognition (95.20% F-score), localization (90.62% F-score), and efficiency (243.85 milliseconds per model).

### III. WORKING OF AI MODEL

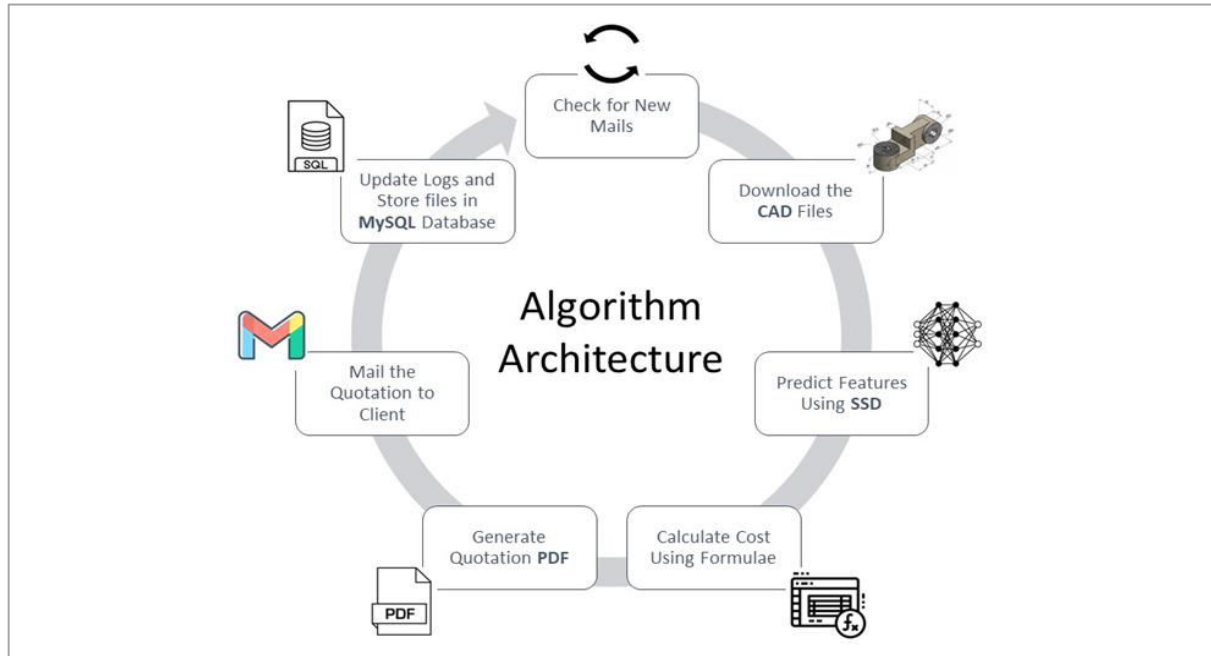


Figure 2 Algorithm Architecture of model

The process of generating machining cost quotes in response to client requests typically involves manual effort and can be time-consuming. Automating this process can greatly enhance productivity and accuracy. The proposed system aims to automate the workflow from quote request detection to quotation generation, optimizing the overall process.

Following are the steps which our AI model follows

Email scan:

The system actively monitors a specified email account, constantly scanning for incoming messages. This ensures that quote requests from clients are promptly identified and processed.

Quote request detection:

Upon receiving an email, the system examines the subject line for the presence of the keyword "#quote." Additionally, it checks for the attachment of one or multiple STL files, which are commonly used in CAD design. If these conditions are met, the system identifies the email as a quote request for CAD machining.

Download files:

The system automatically downloads the attached STL files from the client's email and stores them in a designated "Staging Area" folder. This step prepares the files for further processing.

File conversion:

To enable accurate prediction and analysis, the STL files are converted into the required binvox format using the SSD Net standards. The binvox format allows for precise volume calculations and facilitates the identification of machining features.

Machining feature detection and localization:

A deep learning-based object recognition method called SSD Net is used to analyse the transformed CAD files. The objective of SSD is to quickly and precisely locate objects inside a picture. SSD is a one-shot method that incorporates object localisation and classification into a single network, in contrast to conventional object detection methods, which need numerous phases. A deep convolutional neural network (CNN) serves as the foundation for SSD to do this. The network is built to anticipate a collection of bounding boxes along with the class labels that go with them at various sizes and aspect ratios. It separates the input image into a grid of cells and entrusts the task of identifying objects of

varying sizes and shapes to each cell. One of SSD's major benefits is its Efficacy and quickness. By explicitly anticipating item positions, it eliminates the need for computationally costly region proposal approaches, enabling real-time object detection capabilities. SSD's anchor boxes and multi-scale feature maps enable it to handle objects of various sizes with ease. The system can precisely forecast the precise machining operations necessary for the given CAD design by training SSD Net on a dataset of machining characteristics.

#### Cost and time estimation:

Based on the predicted machining features and the volume of material to be machined, the system calculates the estimated cost and time required for the machining process. This estimation takes into account factors such as material cost, machine time, and labour costs.

#### Quote generation:

Using the gathered information, the system generates a detailed quotation in PDF format. The quotation includes a breakdown of costs, machining features, and a project timeline. This provides the client with a comprehensive understanding of the pricing and expected duration of the machining project.

#### Record logging:

To prevent reprocessing of previously handled emails, the system maintains a CSV log file. This log file stores the filenames and unique identifiers (UID) of processed emails. The system updates the log file whenever a new email is successfully processed.

#### Archiving files:

To ensure easy retrieval and access to historical data, the system compresses the received and generated files into a zip file. The zip file is then stored in a local MySQL server, allowing for efficient storage and retrieval of past machining projects.

## IV. RESULTS AND DISCUSSIONS

Cost estimation and costing are critical for manufacturing industries. Cost estimation should be quick and accurate. Cost is generally classified as to how they vary with the quantity being manufactured.

#### Formulas:

- 1)  $\text{rpm} = \text{cutting speed} * 1000 / 3.14 * \text{diameter}$  (Diameter is tool tip diameter)
- 2)  $\text{feed/min} = \text{rpm/min} * \text{feed/rev}$
- 3)  $\text{time in min} = \text{total cut length} / \text{feed per min}$
- 4)  $\text{total time} = \text{time in min} + \text{tool positioning time}$
- 5)  $\text{machining rate per min @ 7 per min} = \text{total time} * 7$

•Below are the machining cost calculations for a sample that we used as test subject, we requested the local vendor to provide us with the breakdown of quote of sample, discount and GST are not included in the code

#### •Feature no.1: Blind hole

- 1)  $\text{rpm/min} = 20 * 1000 / 3.14 * 12 = 530.79$
- 2)  $\text{feed/min} = 530.79 * 0.12 = 63.69$
- 3)  $\text{time in min} = 382 / 63.9 = 6$
- 4)  $\text{total time} = 6 + 0.1 = 6.1$
- 5)  $\text{machining rate per min @ 7 per min} = 0.57 * 7 = 4$

#### •Feature no.2: Round

- 1)  $\text{rpm/min} = 12.7 * 1000 / 3.14 * 12.7 = 551.68$
- 2)  $\text{feed/min} = 551.68 * 0.4 = 220.67$
- 3)  $\text{time in min} = 100 / 220.67 = 0.45$
- 4)  $\text{total time} = 0.45 + 0.1 = 0.55$
- 5)  $\text{machining rate per min @ 7 per min} = 0.55 * 7 = 3.87$



- Overhead=  $64.38 \times 0.1 = 6.438$
- Handwork=  $64.38 \times 0.1 = 6.438$
- Profit=  $64.38 \times 0.132 = 8.49$
- Total cost= cost + overhead + handwork + profit  
 $= 64.38 + 6.438 + 6.438 + 8.49$   
 $= 85.75 \text{ INR}$

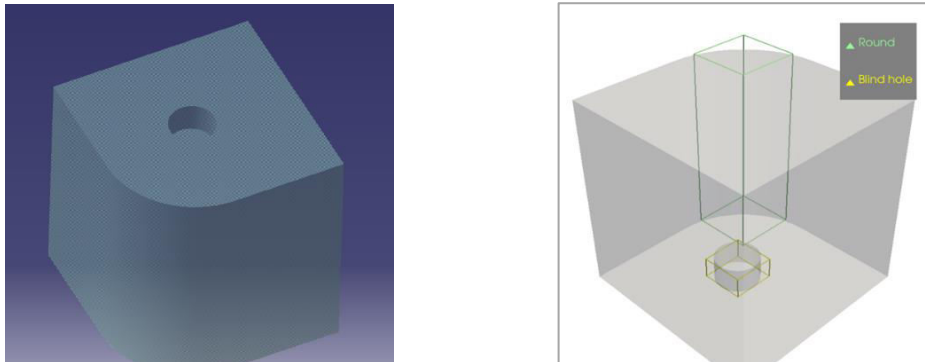


Figure 3 CAD file provided by customer(left) and Machining feature recognized(right)

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a default theme colormap without matplotlib. The builtin VTK "jet" colormap will be use
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Component 1: volume=38197195109.571144, centroid=[5.50632911e+04 5.50632911e+04 3.1500000
Component 2: volume=4412017789.554895, centroid=[3.28424658e+05 3.01164384e+05 3.50000000
Component 1: volume=947616807156.5919, centroid=[325415.20505134 325542.12641112 316303.
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 2.00000000e+00]]
Operation Cutting Speed\n(in m/min) Rate\n(Rs/min) Time\n(in min) Cost\n(Rs)
1 19.0 20.0 7.0 7.46 70.50
2 2.0 22.0 7.0 1.60 15.12
    
```

Index	Operation	Cutting Speed (in m/min)	Rate (Rs/min)	Time (in min)	Cost (Rs)
1	Round	20.0	7.0	7.46	70.5
2	Blind hole	22.0	7.0	1.6	15.12
Sub-Total					85.62
Discount					-8.562
Tax					10.274
<b>Total</b>					<b>87.332</b>

Signature

Figure 4 Code snippet of script estimating cost and sample invoice generated for job

## V. CONCLUSION

In conclusion, our proposed model, a Deep Learning-based Convolutional Neural Network (CNN), has demonstrated remarkable success in estimating manufacturing costs and predicting machining features. With an impressive accuracy rate of 95% for predicting all 24 machining features, our model proves its capability to effectively capture and analyse the intricacies of the manufacturing process.

Moreover, our model achieves a remarkable accuracy rate of 99.8% in predicting the cost associated with machining. To validate the accuracy of the cost predictions, we compared them with the vendor's quotes for the same job, resulting in a strong correlation of 94.8%. This validation provides solid evidence of our model's ability to provide reliable.

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