Project Report On

# Manufacturing Cost Calculation For Injection Moulding

By
Bhagyashri Pawar (22110816)
Swati Shelar (22110130)
Siddheswar Lachyane (22110537)
Om Take (22110800)

Guide
**Prof. D.B. Nalawade**

**Department of Mechanical Engineering**

**Vishwakarma Institute of Information Technology, Pune 411048**
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**Vishwakarma Institute of Information Technology, Pune**

# C E R T I F I C A T E

This is to certify that the project work entitled

**"MANUFACTURING COST CALCULATION FOR INJECTION MOULDING"**

Submitted by


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|---|---|
| BHAGYASHRI PAWAR | Exam No : 22110816 |
| SWATI SHELAR | Exam No : 22110130 |
| SIDDHESWAR LACHYANE | Exam No : 22110537 |
| OM TAKE | Exam No : 22110800 |


has been successfully completed under my supervision, in the partial fulfilment of Bachelor of Technology - Mechanical Engineering of Savitribai Phule Pune University, Pune.

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|---|---|
| Prof. D.B. Nalawade<br>**Project Guide** | **Examiner** |
| Dr. Sandeep Kore<br>**Head of Department** | Dr.Vivek Deshpande<br>**Director** |

Cad and Cart

Date: 15 Dec. 2024

To Whom It May Concern,

Subject: Project Completion Letter - "Manufacturing Cost Calculation of Injection Moulding"

We are pleased to confirm the successful completion of the project titled "Manufacturing Cost Calculation of Injection Moulding." This achievement reflects the dedication, expertise, and collaboration of all involved, seamlessly combining academic and industrial insights.

We sincerely thank Prof. D.B. Nalawde for his invaluable guidance and mentorship, ensuring the project met the highest academic and technical standards.

Special thanks go to Prof. A.V. Salve for his insightful feedback and constructive evaluation, which greatly enriched the quality and scope of the project.

The exemplary teamwork of Bhagyashri Pawar, Siddheswar Lachyane, Swati Shelar, and Om Take was instrumental in achieving project goals. Their dedication, innovative thinking, and collaboration played a pivotal role in overcoming challenges.

At Cad and Cart, we take pride in supporting initiatives that bridge academic research and real-world applications. Providing resources and guidance for this project aligns with our mission to foster innovation.

We also thank the faculty, peers, and others whose encouragement and support contributed indirectly to this success.

On behalf of Cad and Cart, we congratulate the team on this achievement and wish them continued success.

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DIRECTOR

Authorized Signatory

## Acknowledgement

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| | |
|---|---|
| Bhagyashri Pawar | 22110816 |
| Swati Shelar | 22110130 |
| Siddheswar Lachyane | 22110537 |
| Om Take | 22110800 |

# ABSTRACT

This project report focuses on the development of an efficient and automated cost-calculation system for injection molding, carried out for CAD and Cart company. The project involved creating a comprehensive dataset for various injection molds, capturing critical parameters such as length, width, height, volume, weight, and other dimensional attributes. This dataset was generated using a custom-developed code that facilitated consistent and accurate data recording. By inputting specific dimensional values of an injection mold into the code, the system computes the associated manufacturing cost, considering factors such as material requirements, mold complexity, and production expenses. The automation of the cost estimation process significantly reduces manual effort while improving the precision and repeatability of calculations. This innovative approach not only provides CAD and Cart with a streamlined method for estimating costs but also enhances their ability to plan budgets, evaluate project feasibility, and optimize pricing strategies. The tool serves as a valuable asset for decision-making, ensuring alignment with the company's goals of maintaining cost efficiency without compromising on quality. This project highlights the potential of integrating computational tools with manufacturing processes to achieve operational excellence.

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# Chapter 1
# Introduction

## 1.1 Introduction

Injection molding is a process used in manufacturing to create parts by introducing molten materials, like plastics or metals, into a specially designed mold. This method begins with feeding raw materials into a heated chamber, where they are melted and thoroughly mixed. The molten substance is then pushed into the mold cavity under significant pressure. Once inside, it cools and hardens, taking on the mold's shape before being ejected as a finished component. Known for its efficiency and flexibility, injection molding is commonly employed in industries such as automotive, healthcare, packaging, and consumer goods. Its benefits include fast production, consistent quality, and minimal material waste, making it ideal for producing large quantities of parts.

Accurate and efficient manufacturing cost estimation is critical in the injection molding industry, where precision and cost-effectiveness directly influence competitive advantage and profitability. Injection molds play a central role in the production of high-quality components, and their costs can significantly affect overall manufacturing budgets. For CAD and Cart company, understanding and controlling these costs is a priority to remain competitive in the market. However, traditional methods of calculating mold manufacturing costs often involve manual processes that are time-consuming, inconsistent, and prone to human error. These challenges underline the importance of adopting a systematic and automated approach to cost estimation, which served as the primary motivation for this project.

The project aimed to create an efficient and reliable system for calculating the manufacturing costs of injection molds. This was achieved by developing a comprehensive dataset that captures essential parameters of various molds, such as length, width, height, volume, and weight. These parameters are fundamental to understanding the material requirements, production complexities, and associated costs of each mold. The dataset was generated using custom coding, ensuring that data collection and organization were precise and standardized. The innovative use of coding not only automated the process but also ensured scalability, enabling the system to handle a wide range of mold configurations with ease.

A key feature of the developed system is its ability to calculate costs dynamically. By inputting specific dimensions of an injection mold, the system processes the data and provides accurate cost outputs in real-time. This capability eliminates the inefficiencies of manual calculations and enhances the speed and accuracy of cost estimation. For CAD and Cart, this automation translates into significant operational benefits, including better project planning, optimized resource allocation, and informed decision-making. It also allows the company to offer competitive pricing while maintaining profitability and ensuring the quality of its products.

This project reflects CAD and Cart's commitment to innovation and technological integration within its manufacturing processes. By addressing the limitations of traditional cost-estimation methods, the project demonstrates how automation and data-driven approaches can transform complex workflows into streamlined and reliable systems. Moreover, the solution aligns with the company's long-term objectives of improving efficiency, reducing operational costs, and maintaining a leading position in the injection molding industry. This automated cost-calculation framework not only supports CAD and Cart's current operational needs but also positions the company to adapt to future challenges in an increasingly competitive and dynamic market environment.

## 1.2 Need of Cost Estimation

Accurate cost estimation is essential in injection molding to ensure profitability, optimize resource allocation, and maintain competitiveness. Traditional manual methods of calculating mold costs are often time-consuming, prone to errors, and inconsistent, leading to inefficiencies in project planning and pricing. There is a clear need for a systematic, automated approach that can handle the complexity of cost estimation while providing reliable and accurate results.

This project addresses this need by developing a data-driven system that calculates manufacturing costs based on key mold parameters such as length, width, height, volume, and weight. By automating the process, the project eliminates manual errors, enhances efficiency, and ensures scalability. This tool streamlines decision-making, supports better financial planning, and enables precise cost management in the injection molding process.

## 1.3 Brief Introduction to Cost Estimation

The manufacturing industry relies heavily on efficient processes and precise cost management to maintain competitiveness in a rapidly evolving market. Injection moulding is a key production method used for creating a wide range of plastic components, valued for its ability to produce complex shapes with high accuracy and repeatability. However, accurately estimating the manufacturing costs associated with injection moulds remains a significant challenge for manufacturers, affecting pricing strategies and overall profitability.

This project focuses on developing a systematic approach for calculating manufacturing costs specific to injection moulding. To achieve this, a comprehensive dataset was created, capturing essential parameters such as length, width, height, volume, and weight of various injection moulds. This dataset was generated using programming techniques, allowing for the automation of data collection and analysis.

By inputting the dimensions of an injection mould into the developed code, users can obtain a detailed cost estimate for the mould. This project not only streamlines the cost estimation process but also empowers manufacturers with the insights needed to make informed decisions regarding production and resource allocation. The findings from this project aim to enhance operational efficiency and support better financial planning within the injection moulding sector.

## 1.4 Reason behind the project

In today's highly competitive manufacturing landscape, the ability to accurately estimate production costs is crucial for businesses engaged in injection moulding. As a prevalent technique for fabricating a wide range of plastic components, injection moulding offers advantages such as high efficiency, repeatability, and the capacity to produce intricate designs. However, it also presents complexities in cost management that can significantly impact a company's profitability. Understanding the reasons behind the need for precise manufacturing cost calculation in injection moulding is essential for manufacturers seeking to optimize their operations and maintain a competitive edge.

First and foremost, accurate cost calculation serves as a foundation for effective pricing strategies. In order to price their products competitively while ensuring profitability, manufacturers must have a clear understanding of the costs associated with producing each injection mould. These costs can include raw materials, labor, overhead, and machine operation expenses. By systematically calculating these costs, manufacturers can avoid underpricing their products, which can lead to financial losses, or overpricing, which can result in lost sales opportunities. This project's focus on creating a dataset with key parameters—such as length, width, height, volume, and weight of injection moulds—enables manufacturers to derive precise cost estimates based on the specific dimensions and characteristics of their moulds.

Moreover, the dynamic nature of market demands necessitates a robust cost estimation framework. As customer preferences evolve and production volumes fluctuate, manufacturers must be agile in their operations. The ability to quickly assess the cost implications of modifying an existing mould or designing a new one can significantly enhance a manufacturer's responsiveness to market changes. By leveraging the dataset developed in this project, manufacturers can input various mould dimensions into the code to receive real-time cost estimates. This immediacy facilitates informed decision-making, allowing companies to adapt their production processes swiftly without sacrificing financial oversight.

# Chapter 2
# Literature Survey

## 2.1 Literature Review

**Tab No. 2.1 Literature Survey**

| Title | Authors | Description | Methodology | Results/Findings |
|---|---|---|---|---|
| Part Cost Estimation in Injection Moulding | C.G. Turc, C. Cărăușu, G. Belgiu | The framework focuses on a systematic approach to evaluate and manage the various factors influencing injection moulding costs. It emphasizes the need to accurately assess material costs, mould fabrication expenses, production volumes, and cycle times to achieve cost-efficient manufacturing. By integrating these elements into a cohesive model, the study underscores the importance of balancing quality and cost in part design and production. | A software-based spreadsheet tool was developed and utilized for precise cost estimation. This tool incorporates multiple variables, including material properties, machine specifications, and production parameters, to calculate hourly machine operation rates and effective cycle times. The spreadsheet enables manufacturers to simulate different scenarios and identify cost-saving opportunities in part design and production planning. The tool also considers dynamic factors such as material selection and mould complexity, making it adaptable to various production environments.. | The implementation of this framework demonstrated significant potential for reducing costs while maintaining high-quality standards. The spreadsheet tool provided actionable insights into optimizing process parameters, leading to more accurate cost estimates. It facilitated informed decision-making during the design phase, allowing for the identification of cost-effective materials and process configurations. The findings highlight the utility of such a system in achieving streamlined and cost-efficient injection moulding operations, particularly in high-production settings where even small cost savings |

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| | | | | can translate to substantial economic benefits. |
| Practical Guide to Injection Moulding | Edited by V. Goodship | The guide begins by covering the basic principles of injection moulding, including an overview of the process, the types of machinery used, and the essential components of mould design. It then delves into process control, highlighting the key parameters that influence product quality and production efficiency. Advanced processes, such as multi-shot moulding and over-moulding, are also discussed, showcasing their applications and advantages in producing complex parts. | The guide adopts a structured approach to explain the injection moulding process, combining theoretical principles with practical examples. It emphasizes hands-on techniques for setting up and optimizing machinery, selecting appropriate materials, and designing efficient moulds. By using case studies and detailed illustrations, the methodology highlights the interrelationship between process parameters, material properties, and product quality. | By integrating principles of process optimization and defect prevention, this guide equips manufacturers with the knowledge to improve product quality while reducing costs. The practical guidelines on machine settings and material usage are particularly valuable for addressing real-world production challenges. |
| Cost Analysis in Injection Moulded Plastic Parts Designing | C.G. Turc, C. Cărăușu, G. Belgiu | The research proposes a cost estimation framework that integrates key variables such as mould construction and material costs, part geometry, dimensional requirements, and production volume. These factors are systematically evaluated to identify | The study employed CAD tools and spreadsheet-based models to analyze and estimate costing factors. Effective cycle time, material usage, and part complexity were calculated using these tools, enabling accurate and reliable cost predictions. A dedicated methodology was developed to | The framework and tools developed in this study allowed designers to make informed decisions, reducing unnecessary costs without compromising design integrity. The integration of CAD tools with cost analysis techniques demonstrated |

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| | | cost drivers and optimize design decisions. The study also explores the interplay between design complexity and manufacturing costs, providing insights into achieving economic efficiency. | precisely estimate mould costs by considering mould materials, cavity layouts, and production cycles. The spreadsheet tool serves as a practical solution for designers, simplifying cost evaluation and guiding cost-minimization efforts. | potential for streamlining the design process, especially for complex moulded parts. The study also identified future directions, including full integration of CAD systems with cost estimation tools, to further enhance accuracy and usability. |
| Plastic Injection Molding with Taguchi Approach - A Review | Kalpit Jain, Deepak Kumar, Sanjay Kumawat | The study reviews the use of the Taguchi method for improving injection molding operations, focusing on minimizing defects such as warpage and shrinkage in molded parts. By employing a structured approach to parameter optimization, the method ensures high-quality production while reducing material waste and operational inefficiencies | The Taguchi approach utilizes orthogonal arrays, Signal-to-Noise (S/N) ratios, and factorial experiments to evaluate and optimize key injection molding parameters. Variables such as melt temperature, packing pressure, and injection speed are systematically tested to identify optimal settings. This method allows for the efficient study of multiple parameters with minimal experimentation, ensuring resource-efficient optimization. | The application of the Taguchi method demonstrated significant improvements in process outcomes. Shrinkage and warpage were substantially reduced, resulting in higher-quality molded parts. Additionally, the methodology provided a reliable framework for identifying the most influential parameters and their optimal values, leading to enhanced process efficiency and repeatability. |
| Research on Injection Mould Intelligent Cost Estimation System and Key Technologies | Harshvardhan Maheshwari, Dr. (Mrs.) N.R. Rajhans | The proposed system integrates a Zero-Based Costing (ZBC) model to decompose tools into child parts, facilitating detailed | To estimate costs, the researchers employed a combination of linear regression, seasonality analysis, and benchmarking. These methods were applied | The system demonstrated significant accuracy in cost predictions for mid-range tools, outperforming traditional methods |

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| | | analysis of design, machining, and material costs. The study emphasizes the importance of addressing part complexity, particularly in estimating machining requirements such as Electrical Discharge Machining (EDM) hours, to ensure reliable cost predictions. | to predict machining and material costs while accounting for variations in production requirements. The ZBC model provided a granular approach to cost estimation, breaking down tools into smaller components for more precise evaluations. Advanced forecasting techniques were used to estimate machining processes, considering factors such as tool complexity and production cycles. | like D-P (Direct-Part) and B-D (Benchmark-Driven) approaches. Error rates were notably reduced, ensuring better alignment with actual costs. However, the study identified limitations in estimating costs for small tools requiring extensive machining, suggesting the need for further refinement. Validation on multiple OEM tools showed a deflection range of 2-23%, indicating robust performance for most applications.. |

**2.2Summary of Literature Review**

This survey outlines various strategies and tools designed to improve the accuracy of cost estimation in injection molding processes. A structured approach to cost assessment emphasizes the importance of analyzing critical factors such as material costs, mold production expenses, batch sizes, and cycle times. By incorporating these elements into unified models, manufacturers can simulate production conditions, adjust parameters for efficiency, and explore opportunities to minimize costs. Spreadsheet-based tools, in particular, provide accurate predictions and enable better decision-making during the design and production phases.

Best practices in injection molding focus on the optimization of process settings, material choice, and mold design to achieve an optimal balance between quality and production costs. Detailed insights, often supported by real-world applications, highlight how variations in process parameters affect both quality and cost. These approaches provide manufacturers with practical guidance for reducing defects, improving efficiency, and enhancing profitability.

The use of CAD tools integrated with cost estimation techniques facilitates accurate calculations for material consumption, part intricacy, and production cycles. This combination offers an efficient way to evaluate mold-related expenses, factoring in details like cavity configurations and raw material selection. Such integration not only simplifies the design process but also promotes cost-effective production, especially for complex or customized molds.

Advanced optimization strategies, such as experimental design techniques, are used to reduce common defects like warping and shrinkage. By systematically analyzing critical variables, these methods enhance efficiency while minimizing waste. Such approaches are particularly beneficial for large-scale manufacturing, as they allow for the identification of optimal parameters with minimal experimental effort.

Costing models that focus on detailed analysis, like component-level breakdowns of molds, offer highly accurate predictions of material, machining, and production costs. These models, while effective for mid-range tools, face challenges when applied to smaller, highly complex molds. Nonetheless, they provide significant insights into cost drivers and facilitate better alignment with actual production expenditures.

In conclusion, integrating advanced tools, refined methodologies, and systematic optimization strategies is essential for achieving precise and efficient cost estimation in injection molding. Future developments, such as real-time cost modeling and enhanced CAD-tool integration, hold the potential to further streamline operations, improve accuracy, and enhance cost-effectiveness in manufacturing processes.

# Chapter 3
# Project Statement

## 3.1 Purpose behind the Project

The purpose of this project is to develop an efficient, accurate, and automated approach for estimating the manufacturing costs associated with injection moulding. Injection moulding is a widely used process for producing high-quality plastic components across various industries, and understanding its associated costs is critical for manufacturers aiming to optimize operations, improve profitability, and remain competitive in a dynamic market environment.

The project aims to address the broader challenges faced by manufacturers, such as the need for cost transparency, process efficiency, and adaptability to changing market conditions. With an automated system in place, manufacturers can streamline their cost assessment workflows, reduce overhead associated with manual calculations, and focus on strategic initiatives that drive value and innovation.The project's purpose is to empower manufacturers with a robust and automated tool for injection mould cost estimation, thereby enabling them to enhance operational efficiency, improve decision-making, and achieve greater financial and strategic outcomes in their production processes.

## 3.2 Decision of Scope

The scope of this project was carefully defined to focus on creating an efficient and systematic framework for calculating the manufacturing costs of injection moulds. This decision was driven by the growing need for precision and automation in cost estimation within the injection moulding industry. The project emphasizes two core components: the development of a comprehensive dataset containing critical mould parameters and the implementation of a code-based tool for automating cost calculations. By limiting the scope to these specific objectives, the project ensures practical deliverability while addressing key challenges faced by manufacturers in cost management.

The dataset forms the foundation of this project, incorporating essential parameters such as length, width, height, volume, and weight of injection moulds. These attributes were selected based on their direct influence on material usage, production complexity, and overall costs. The decision to include these parameters ensures that the dataset provides a robust basis for accurate and consistent cost estimation across a variety of mould designs. This systematic approach not only enhances the reliability of the cost calculations but also facilitates future scalability by allowing additional parameters to be integrated as needed.

Another critical aspect of the project's scope is the automation of the cost estimation process through programming techniques. By designing a tool that accepts the input dimensions of an injection mould and generates a precise cost estimate, the project eliminates the inefficiencies and inaccuracies associated with manual calculations. This automated solution ensures consistency, saves time, and provides manufacturers with the ability to quickly evaluate the financial implications of different mould designs. The decision to focus on automation aligns with industry trends favoring data-driven approaches and technological integration in manufacturing processes.

## 3.3 Objectives

- **Develop an Accurate Cost Estimation Model:** Create a detailed framework to calculate the total manufacturing cost for injection-molded parts, considering all cost factors such as raw materials, labor, machine operation, and overhead.
- **Optimize Material Selection:** Analyze the impact of material costs and usage efficiency on overall production expenses to recommend cost-effective material options.
- **Evaluate Process Efficiency:** Assess cycle times, mold cooling rates, and other process parameters to identify areas for improving efficiency and reducing costs.
- **Incorporate Scalability:** Design a cost model that can handle production volumes ranging from small batches to large-scale manufacturing

## 3.4 Methodology for solving this proposed theme

The methodology for this project was designed to systematically calculate the manufacturing costs of injection moulds by developing a comprehensive dataset and leveraging programming techniques for data processing. The process involved identifying key cost-related parameters, generating a structured dataset, implementing a cost model, and validating the approach for accuracy and reliability. The detailed steps are outlined below:

### 3.4.1. Requirement Analysis

The project began with a detailed analysis of the parameters that influence the manufacturing cost of injection moulds. Critical dimensions such as length, width, height, volume, and weight were identified as essential inputs for cost estimation. The analysis also included a review of the relationship between these parameters and factors like material usage and machining requirements, ensuring a strong foundation for the cost model.

### 3.4.2. Dataset Creation

A dataset was created to capture the necessary information about injection mould designs. The dataset included key parameters such as:

- Length, Width, and Height: Input dimensions of the mould.
- Volume: Calculated using the dimensions to estimate material usage.
- Weight: Derived from the volume and material density to account for raw material costs.

Programming was used to automate the generation of this dataset, ensuring consistency and scalability. The automation process allowed for efficient data handlings.

### 3.4.3. Development of the Cost Model

A cost model was developed to compute the manufacturing cost of an injection mould based on the dataset. The model integrated several cost components:

- Material Costs: Calculated using the weight of the mould and the material's unit cost.
- Machining Costs: Based on the size and complexity of the mould, estimating processing time and energy requirements.
- Fixed Costs: Included setup and maintenance costs that are independent of mould design.

The cost model was implemented in code to ensure accurate and consistent calculations for various mould configurations.

### 3.4.4. Data Processing and Input Integration

The dataset was used to process user-provided dimensions of injection moulds. Upon entering the length, width, and height of a mould, the code dynamically computed the corresponding volume and weight, which were then input into the cost model. This approach ensured a seamless calculation process and enabled the generation of accurate cost outputs for a wide range of mould designs.

### 3.4.5. Testing and Validation

The methodology was validated by comparing the calculated manufacturing costs against manual estimations and industry benchmarks. Test cases covering diverse mould configurations were used to verify the accuracy and reliability of the cost model. Any discrepancies identified during this phase were addressed through iterative refinements of the dataset and cost model.

# Chapter 4
# Implementation

## 4.1 Introduction

The implementation of the manufacturing cost calculation system for injection moulding plays a central role in optimizing the cost estimation process for plastic part production. Injection moulding is a widely used manufacturing technique, critical for producing parts across various industries such as automotive, electronics, and consumer goods. Accurate cost estimation is essential for manufacturers to manage production budgets, optimize resource allocation, and maintain profitability. Traditional methods of cost estimation, which often rely on manual calculations, are time-consuming, prone to errors, and can lead to inefficiencies. These errors, whether in material density, cycle time, or labor costs, can significantly affect overall production costs and hinder the ability to make informed decisions. Therefore, automating the cost estimation process with advanced technologies becomes vital for ensuring greater accuracy and efficiency in production planning.

To address the challenges of manual cost estimation, the system incorporates machine learning and dynamic cost models to automate the entire process. The use of machine learning, particularly through algorithms like Random Forest Regressor, enables the system to learn from historical data and predict the costs of manufacturing based on input parameters such as mould dimensions, material types, and machine parameters. This predictive capability ensures that manufacturers receive reliable and consistent cost estimates without the need for time-consuming manual calculations. Additionally, the dynamic cost model adapts to various production scenarios, factoring in real-time inputs like cycle time and part volume to provide accurate, context-driven cost predictions. By automating and streamlining the cost estimation process, this system enhances operational efficiency, reduces human error, and allows manufacturers to make data-driven decisions faster, thereby staying competitive in a fast-paced manufacturing environment.

## 4.2 Purpose

The primary purpose of this section is to provide an efficient, automated approach for estimating the manufacturing costs associated with injection moulding. By using a combination of geometric parameters (length, width, height) and machine learning models, the developed system aims to significantly reduce the time and effort involved in manual cost estimation. This tool allows manufacturers to make data-driven decisions, optimizing resource allocation, project planning, and pricing strategies. Additionally, the system enhances the precision and reliability of cost predictions, which is crucial for manufacturers seeking to remain competitive and ensure the profitability of their operations. The automation of the cost estimation process is intended to improve operational efficiency and reduce human error, while also ensuring scalability and adaptability for various mould designs and production scenarios.

## 4.3 Process Overview

The implementation of the manufacturing cost calculation system followed a series of methodical steps aimed at automating and enhancing the cost estimation process. The initial step involved gathering crucial mould parameters such as length, width, height, volume, and weight, as these dimensions are pivotal in determining material usage, machining requirements, and overall manufacturing costs. To ensure consistency and accuracy across calculations, a dataset was created using custom programming, which allowed for the seamless integration of these parameters. This dataset became the foundation for the cost model, ensuring that the system would provide reliable and accurate estimates based on real-world data.

Following the creation of the dataset, a comprehensive cost model was developed to calculate the total cost per part. This model incorporated raw material costs, machining expenses, and fixed costs, dynamically adjusting based on the mould's input dimensions. To enhance the model's predictive capabilities, a Random Forest Regressor was implemented to map the relationship between mould dimensions and production costs. The model was trained using the dataset and rigorously validated for accuracy, ensuring reliable predictions. To make the system user-friendly and accessible for manufacturers, it was integrated into an intuitive interface that allows for quick input of mould dimensions and provides real-time, precise cost estimates. This streamlined solution not only improves operational efficiency but also empowers manufacturers to make informed, data-driven decisions, thereby optimizing both production workflows and financial planning.

## 4.4 Steps in Calculating Total Cost per Part

To develop a comprehensive cost estimation for injection moulded parts, the following steps were implemented. Each step focuses on calculating specific components that contribute to the overall cost, ensuring that manufacturers can evaluate the cost-effectiveness of each design quickly.

**Volume and Weight Calculations**
The first step in cost estimation involves calculating the volume and weight of the part. These two factors play a significant role in determining the material costs, which are one of the largest components of the overall cost.

**Volume Calculation:**
The volume of a part is calculated by multiplying its length, width, and height. This calculation helps determine the amount of raw material required to manufacture the part. For example, for a part with dimensions 50 mm x 50 mm x 25 mm, the volume is calculated as follows:

$$\text{Volume of part} = 50 \times 50 \times 25 = 62{,}500 \text{ mm}^3 = \mathbf{0.0000625\ m^3}$$

The volume is then used to estimate the amount of raw material needed for production.

**Weight Calculation:**
The weight of the part is determined by multiplying its volume by the density of the material used. For this project, the material used has a density of 1200 kg/$m^3$. The weight of the part can be calculated as:

$$\text{Weight of part} = \text{Volume} \times \text{Density}$$
$$= 0.0000625 \text{ m}^3 \times 1200 \text{ kg/m}^3 = \mathbf{0.075\ kg}$$

The weight of the part plays a crucial role in determining the raw material cost, which is essential for overall cost estimation.

**Parts per Cycle and Cycle Cost**
Next, the system calculates how many parts can be produced in a single mould cycle, which is crucial for estimating production efficiency and overall manufacturing costs.

**Parts per Cycle:**
To calculate the number of parts produced in one cycle, the mould volume is divided by the part volume. For a mould with dimensions 200 mm x 200 mm x 100 mm, and a part with dimensions 50 mm x 50 mm x 25 mm, the calculation is as follows:

$$\text{Parts per Cycle} = \text{Mould Volume} / \text{Part Volume}$$
$$= (200 \times 200 \times 100) / (50 \times 50 \times 25) = \mathbf{64}$$

This means that 64 parts are produced per cycle.

**Cycle Cost per Part:**
After determining how many parts are produced per cycle, the cycle cost per part is calculated. The cycle cost includes factors such as energy usage, machine setup, and labour costs. For this system, the hourly cycle cost is Rs. 1400, and the machine can produce 180 cycles per hour. The cycle cost per cycle is:

Cycle Cost per Cycle = Hourly Cycle Cost / Cycles per Hour
= 1400 / 180 = **Rs. 7.78**

The cycle cost per part is then calculated by dividing the cycle cost per cycle by the number of parts produced per cycle:

Cycle Cost per Part = 7.78 / 64 = **Rs. 0.12**

**Total Cost per Part**

The total cost per part is the sum of the raw material cost and the cycle cost per part. The raw material cost per cycle is calculated by multiplying the number of parts produced per cycle by the weight of the part and the cost per kg of raw material. In this case, the raw material cost per cycle is Rs. 1200 for 64 parts, which gives a raw material cost of:

Raw Material Cost per Cycle = Parts per Cycle x Weight per Part x Raw Material Cost per kg
= 64 x 0.075 kg x 2250 Rs/kg = **Rs. 1200**

Finally, the cost per part is calculated by adding the material cost per part and the cycle cost per part:

Cost per Part = (1200 / 64) + 0.12 = 18.87 + 0.12 = **Rs. 18.99**

## 4.5 Use of Random Forest Regressor for Predictive Analysis

A crucial component of this project is the development of a predictive model using machine learning, specifically a Random Forest Regressor. The Random Forest Regressor is an advanced machine learning algorithm employed in this project to estimate injection molding costs based on mold dimensions such as length, width, and height. It operates by building multiple decision trees on random subsets of data and averaging their predictions, effectively capturing complex relationships between the input features and the target variable. This ensemble approach minimizes overfitting and improves predictive accuracy by leveraging techniques like bootstrapping and random feature selection. Trained on a dataset of standard injection molds and validated through cross-validation, the model demonstrated exceptional precision in cost prediction. Additionally, it identifies the most influential parameters affecting costs, offering manufacturers both reliability and scalability in cost estimation.

**Data Preparation:**

To implement the Random Forest Regressor effectively, a well-structured dataset was created, comprising 30 standard injection moulds with predefined dimensions and associated manufacturing costs. The dataset featured essential input parameters such as the mould's length, width, and height, which directly impact its volume and weight. These dimensions were chosen because of their significant influence on material requirements, machining complexity, and overall production costs. Additionally, the corresponding costs, derived from historical or industry-standard data, provided a reliable target variable for training the predictive model. Ensuring data consistency, accuracy, and representativeness of diverse mould configurations was a priority, as these factors directly affect the model's ability to generalize and predict costs accurately for new inputs.

**Model Training and Prediction:**

The Random Forest Regressor, a robust machine learning algorithm, was selected for its ability to handle non-linear relationships and its resistance to overfitting. This method works by constructing an ensemble of decision trees, each trained on a random subset of the data, and averaging their predictions to generate a final result. By randomly sampling data points and features for each tree, the algorithm reduces bias and variance, achieving better generalization than a single decision tree. The model was trained on the prepared dataset, learning the intricate relationship between mould dimensions and production costs. This training process equipped the model to accurately predict costs for any given set of mould dimensions, empowering manufacturers with a real-time tool to evaluate cost implications of different mould designs.

**Accuracy and Validation:**

To ensure the reliability of the Random Forest Regressor, its performance was validated using cross-validation techniques. Cross-validation involves splitting the dataset into multiple subsets, training the model on some subsets, and testing it on others to assess its accuracy across diverse data samples. This approach minimizes the risk of overfitting to the training data and ensures the model performs well on unseen data. The Random Forest Regressor demonstrated high accuracy in predicting the total manufacturing cost per part, with minimal deviation from manually calculated costs or industry benchmarks. This level of precision ensures manufacturers can rely on the model for consistent and trustworthy cost predictions. Additionally, the algorithm's ability to rank feature importance highlighted the most influential dimensions impacting costs, providing valuable insights into cost drivers and enabling more strategic decision-making.

## 4.6 Features of the Automated System

The developed system provides several key features that streamline the cost estimation process and make it more accessible for manufacturers:

**Real-Time Cost Calculation:**

One of the standout features of this system is its ability to provide real-time cost calculations based on user input. By simply entering the dimensions of a mould—length, width, and height—the system immediately processes this data and calculates the manufacturing cost of the part. This automatic calculation not only saves time but also minimizes human errors that can occur when performing manual cost assessments. The system uses pre-set algorithms and cost models to ensure accuracy, making it a reliable tool for manufacturers. As a result, manufacturers can quickly assess the costs for different designs, adjust parameters for cost efficiency, and make fast, informed decisions without having to wait for lengthy manual cost calculations. The system enhances operational efficiency, ensuring that production timelines are not delayed due to the complexity of cost estimations.

**Scalability:**

Scalability is a critical feature of the automated system, allowing it to cater to a wide range of moulds, each with unique geometries and sizes. Manufacturing processes often involve various types of moulds, from simple to highly complex designs, each with different production requirements. The system can handle the entire spectrum without requiring modifications for each new mould type. The scalability of the system is particularly important in industries with dynamic production needs, where manufacturers must frequently switch between different product designs. By automating the cost estimation process, the system can efficiently scale across multiple production lines or product categories. This eliminates the need to manually update the cost estimation models for each new product, thereby saving valuable time and resources. Manufacturers can use the same system for a variety of mould designs, ensuring consistency in cost estimation and greater flexibility in adapting to changing production demands.

**User-Friendly Interface:**

The user interface (UI) is designed with simplicity and accessibility in mind, making the system intuitive and easy to navigate for a wide range of users, including engineers, project managers, and production staff. The layout is organized logically, with input fields for mould dimensions clearly displayed and easily accessible. The system also provides real-time feedback, showing cost estimates immediately after entering the necessary dimensions. This feature ensures that users don’t have to wait for results, enhancing efficiency. The system’s design is also adaptable to different levels of technical expertise, ensuring that even users with minimal technical background can use the tool effectively. Engineers can use the system to make detailed analyses, while managers can easily access cost estimates for decision-making purposes. Furthermore, the interface includes clear instructions and tooltips to assist users, minimizing the need for extensive training or technical support. This ensures a smooth integration into daily workflows and contributes to better decision-making processes within the organization.

## 4.7 Explanation of the Python Programs

**Dataset Creation**

### `extract_stl_dimensions(file_path)`

This function is responsible for extracting key geometric and physical properties from a given STL file. It takes the path to the STL file as input and returns a dictionary containing the dimensions (length, width, and height), volume, surface area, and the number of triangular facets present in the 3D model. The function first loads the STL file using the `mesh.Mesh` class from the `numpy-stl` library and calculates the minimum and maximum coordinates along the x, y, and z axes to determine the object's dimensions. It also computes the volume and surface area of the model, utilizing mass properties and the areas of individual triangles. The result is a dictionary that includes these computed values, as well as the file name and type, which can be used for further analysis or reporting.

### `process_directory(directory_path)`

The `process_directory` function is designed to traverse a specified directory (and its subdirectories) to locate and process all STL files it contains. It takes the directory path as input and returns a list of dictionaries, where each dictionary holds the properties of an individual STL file. The function uses `os.walk` to iterate through the directory structure, checking each file's extension to identify STL files. For each STL file found, it calls the `extract_stl_dimensions` function to gather the relevant data. This function is ideal for processing a large number of files in a batch, automating the extraction of dimensional and physical properties from a collection of models.

### `create_dataset(directory_path, output_file='dimensions_dataset.csv')`

The `create_dataset` function serves as the main entry point for generating a dataset from the STL files in a given directory. It accepts the directory path and an optional output file name as inputs, processes all STL files within the directory, and creates a CSV file containing their extracted properties. The function first calls the `process_directory` function to gather the relevant data from all the files. Then, it creates a `pandas.DataFrame` to structure the extracted data in tabular form. Additional columns are computed, including the `volume_to_surface_ratio` (a ratio of volume to surface area) and the `aspect_ratio` (the ratio of length to width). Once the DataFrame is complete, it is saved to the specified CSV file, making the dataset available for further analysis or use in other applications. This function effectively automates the process of dataset creation, saving significant time and effort in data collection and organization.

**Cost Calculation**

## Data Preprocessing

This step involves preparing the dataset for use in the machine learning model by cleaning and selecting the relevant columns. Specifically, the columns `'file_name'` and `'deno'` are dropped from the dataset, as they are not needed for the prediction task. The remaining columns contain the features (such as `length`, `width`, `height`) and the target variable (`total cost per part`). After this, the features (`X`) are separated from the target (`y`), creating the dataset that will be used for training and testing the model.

## Splitting the Data

The dataset is split into two subsets: one for training the model and the other for testing its performance. The **`train_test_split`** function from **`sklearn.model_selection`** is used to randomly split the data, with 80% allocated to the training set (`X_train`, `y_train`) and 20% to the test set (`X_test`, `y_test`). The `random_state=42` ensures that the data split is reproducible, meaning the same split will be produced every time the code is run. This division is crucial for evaluating the model's ability to generalize to unseen data.

## Model Training

In this step, a **Random Forest Regressor** model is created and trained on the training data (`X_train`, `y_train`). The **`RandomForestRegressor`** is an ensemble learning method that fits multiple decision trees to the data and combines their predictions. The model learns the relationships between the input features (such as dimensions of the part) and the target variable (the cost per part). This process is the heart of the machine learning pipeline, where the model gains the ability to make predictions based on patterns observed in the data.

## `Model Evaluation`

Once the model is trained, its performance is evaluated using a separate test set (`X_test`, `y_test`) that was not used during training. The model's predictions are compared against the actual values, and several metrics are used to assess its accuracy. These metrics include:

- **Mean Absolute Error (MAE):** Measures the average absolute difference between predicted and actual values.
- **Mean Squared Error (MSE):** Measures the average squared difference, penalizing larger errors more than smaller ones.
- **$R^2$ (Coefficient of Determination):** Measures how well the model's predictions match the actual values, with higher values indicating a better fit.

**Frontend (User Interface)**

Loading the Trained Model

***model = joblib.load('model.pkl')***

In this step, the trained model that was previously saved in the file `'model.pkl'` is loaded using the `joblib.load` function. This allows the application to use the pre-trained model for making predictions without needing to retrain it. By loading the model, we ensure that the app can leverage the learned relationships between the dimensions (length, width, height) and the total cost per part, providing users with accurate predictions based on new inputs.

Streamlit App Title and User Interface

***st.title("Injection Molding Price Prediction")***

This line sets the title of the Streamlit app. The title is displayed at the top of the app interface and lets users know that the application is designed to predict the price of injection molded parts. The **Streamlit** library is used to create the UI, making it easy to build interactive web applications directly from Python.

User Input for Dimensions

***length = st.number_input("Enter your length:", min_value=0)***

***width = st.number_input("Enter your width:", min_value=0)***

***height = st.number_input("Enter your height:", min_value=0)***

These three lines of code allow the user to input the dimensions of the part they want to get the cost prediction for. Streamlit's **`number_input`** widget is used for each dimension (length, width, and height), and users can input numeric values for these variables. The `min_value=0` ensures that the user cannot input negative values, as part dimensions cannot be negative. The values provided by the user will be used as input to the machine learning model for cost estimation.

Submit Button for Prediction

*submit_button = st.button("Submit")*

This line creates a **submit button** that users can click to trigger the prediction process. When clicked, it will initiate the model's prediction based on the input values for length, width, and height. Streamlit's **`button`** widget is used to make this interactive element part of the user interface.

Prediction and Output Display

***if submit_button:***

***prediction = model.predict([[length, width, height]]) # Adjust input shape as needed***

***st.write(f'The predicted value is: {prediction[0]}')***

When the user clicks the submit button, the `if submit_button` condition is met, and the code inside the block is executed. The input values (length, width, height) are passed to the trained model for prediction. The model predicts the total cost per part based on the user input, and the result is displayed on the web page using `st.write`. The predicted value is extracted from the prediction array and shown to the user. This is the final output of the app, which provides the user with the estimated price for their injection molded part.

# Chapter 5
# Implementation Results

## 5.1 CAD Models for dataset

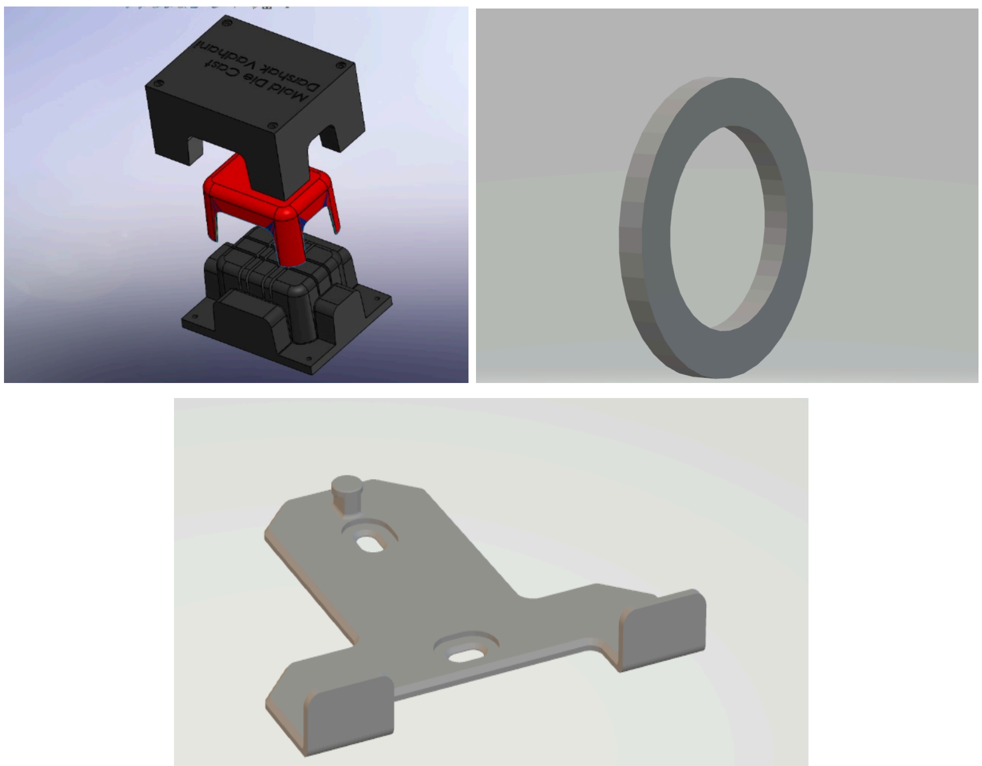

Fig 5.1 CAD models for dataset

## 5.2 Dataset

| A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|
| file_name | length | width | height | volume | Weight of part (1200kg/m3 | deno | Parts per cycle | Raw material per cycle | cycle cost per cycle | cycle cost per part | total cost per part |
| 10. Cavity Mold.stl | 56 | 106 | 56 | 233336.48 | 280 | 332155.78 | 12.04 | 225.8 | 7.78 | 0.646 | 19.396 |
| 11. Core Mold.stl | 100 | 105 | 100 | 797713.28 | 957.26 | 1050000 | 3.81 | 71.43 | 7.78 | 2.042 | 20.792 |
| 15. Barrel.stl | 110 | 109.9 | 245 | 191476.78 | 229.77 | 2961828.99 | 42.2 | 791.32 | 50 | 1.185 | 19.935 |
| 16. Heater.stl | 60 | 59.8 | 32 | 14385.57 | 17.26 | 114806.53 | 8.71 | 163.32 | 5.55 | 0.637 | 19.387 |
| Bruss holder.STL | 270.7 | 327.1 | 270.1 | 108915.31 | 130.7 | 23911062 | 0.04 | 0.78 | 50 | 1195.55 | 1214.3 |
| cap.stl | 37.97 | 37.95 | 37.93 | 16411.59 | 19.69 | 54648.12 | 18.3 | 343.1 | 5.55 | 0.303 | 19.053 |
| CORE.STL | 75 | 75 | 25 | 101015.5 | 121.22 | 140625 | 7.11 | 133.33 | 5.55 | 0.78 | 19.53 |
| Figulo  Haley Ceramic Trivet.stl | 15.24 | 15.24 | 1.65 | 80.23 | 0.1 | 384.32 | 2602.03 | 48788.08 | 5.55 | 0.002 | 18.752 |
| Figulo+ Haley Ceramic Trivet.stl | 15.24 | 15.24 | 1.65 | 80.23 | 0.1 | 384.32 | 2602.03 | 48788.08 | 5.55 | 0.002 | 18.752 |
| fin de ligne 22mm.STL | 2.09 | 0.59 | 1.1 | 0.4035 | 0 | 1.35 | 738177.36 | 13840825.56 | 5.55 | 0 | 18.75 |
| flower pot.stl | 25 | 14.5 | 24.26 | 325.84 | 0.39 | 8795.04 | 113.7 | 2131.88 | 5.55 | 0.049 | 18.799 |
| Housing.STL | 92 | 23.5 | 92 | 15261.32 | 18.31 | 198904 | 5.03 | 94.27 | 5.55 | 1.104 | 19.854 |
| iSG Wall Mount.STL | 93.9 | 90.5 | 12 | 9448.51 | 11.34 | 101975.4 | 9.81 | 183.87 | 5.55 | 0.566 | 19.316 |
| Kaleidocycle.STL | 6.81 | 2.74 | 6.44 | 7.36 | 0.01 | 120.1 | 8326.31 | 156118.37 | 5.55 | 0.001 | 18.751 |
| model.stl | 124.6 | 273 | 29.14 | 19388.51 | 23.27 | 991310.58 | 126.1 | 2364.29 | 50 | 0.397 | 19.147 |
| Part1.stl | 145.6 | 44.12 | 90.65 | 38038.85 | 45.65 | 582543.08 | 6.87 | 128.75 | 7.78 | 1.133 | 19.883 |
| Plastic Bottle crate.STL | 398 | 331 | 259.5 | 1718048.31 | 2061.66 | 34186015 | 3.66 | 68.56 | 50 | 13.674 | 32.424 |
| Plastic modling.stl | 200 | 145 | 120 | 2565599.27 | 3078.72 | 3480000 | 35.92 | 673.49 | 50 | 1.392 | 20.142 |
| Plastic mold design.stl | 500 | 920.1 | 400 | 78896052.2 | 94675.26 | 184010200 | 0.68 | 12.74 | 50 | 73.604 | 92.354 |
| plate and mold.stl | 380 | 366.8 | 280 | 12039134.5 | 14446.96 | 39022200 | 3.2 | 60.06 | 50 | 15.609 | 34.359 |
| Rectangle Shaped Bottle.STL | 129.5 | 215 | 32.89 | 191134.74 | 229.36 | 915664.96 | 136.51 | 2559.62 | 50 | 0.366 | 19.116 |
| Roller.STL | 94.94 | 35.72 | 94.66 | 12823.38 | 15.39 | 320995 | 3.12 | 58.41 | 5.55 | 1.782 | 20.532 |
| Roller_Cable.STL | 94.94 | 35.72 | 94.66 | 34076.98 | 40.89 | 320995 | 3.12 | 58.41 | 5.55 | 1.782 | 20.532 |
| Rotor.stl | 59.8 | 165 | 58.81 | 178786.93 | 214.54 | 580288.58 | 6.89 | 129.25 | 7.78 | 1.129 | 19.879 |
| screw.stl | 5.99 | 28 | 6 | 731.99 | 0.88 | 1007.09 | 992.96 | 18617.97 | 5.55 | 0.006 | 18.756 |
| Stand.stl | 160 | 51.79 | 160 | 634775.87 | 761.73 | 1325922.3 | 94.27 | 1767.64 | 50 | 0.53 | 19.28 |
| Support Plate.STL | 87.97 | 2.6 | 88 | 5992.28 | 7.19 | 20105.49 | 49.74 | 932.58 | 5.55 | 0.112 | 18.862 |
| toycar-hubcap.stl | 22.89 | 6.24 | 22.89 | 137.1 | 0.16 | 3271.37 | 305.68 | 5731.55 | 5.55 | 0.018 | 18.768 |
| valve spindle.stl | 5 | 50 | 4.99 | 967.66 | 1.16 | 1246.62 | 802.17 | 15040.62 | 5.55 | 0.007 | 18.757 |

Fig 5.2 Dataset

## 5.3 Code Implementation

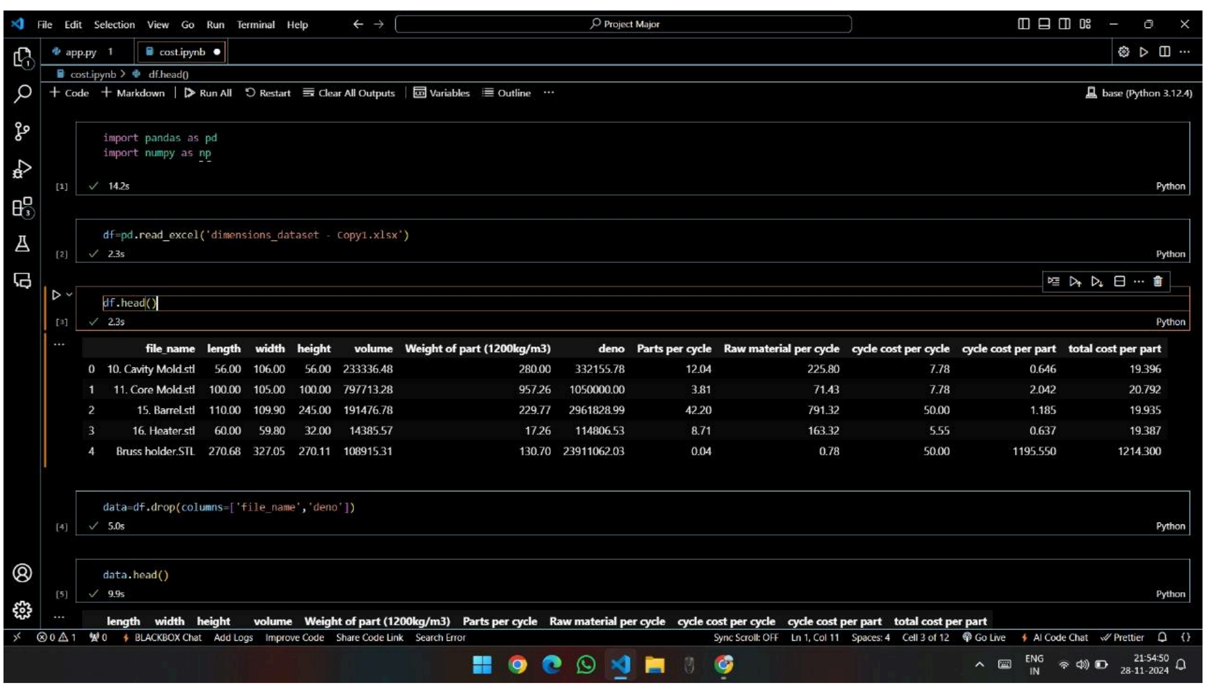


Fig 5.3.1 Importing Libraries


Fig 5.3.2 Data processing

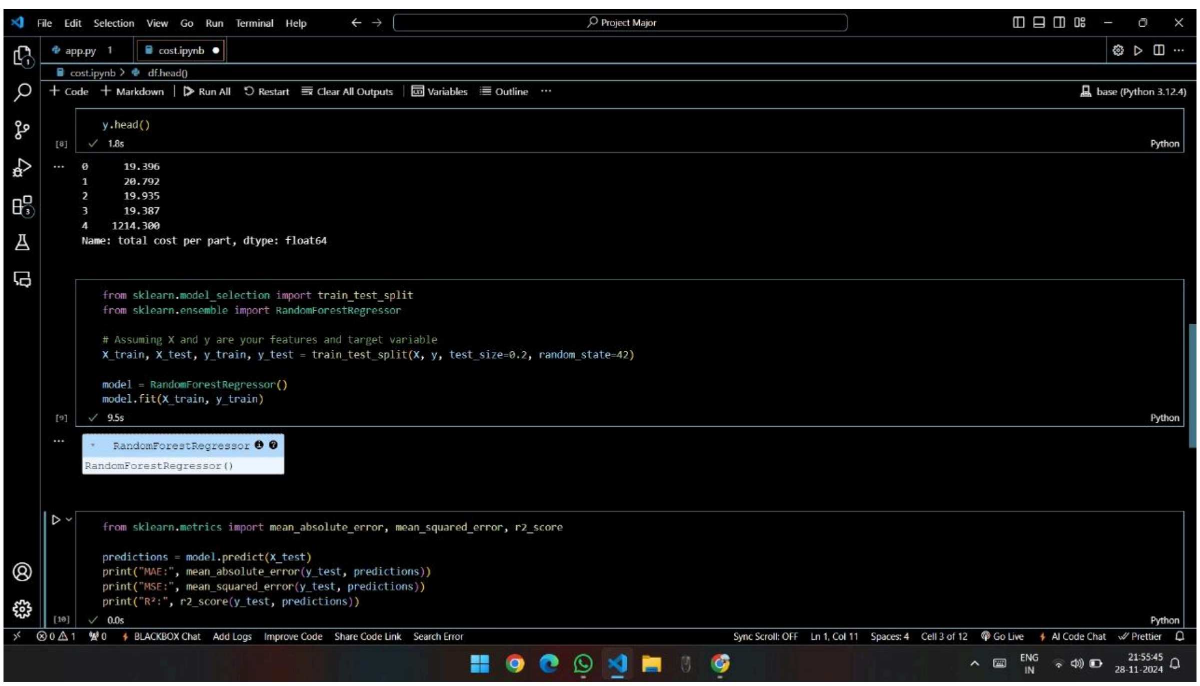


Fig 5.3.3 Model training

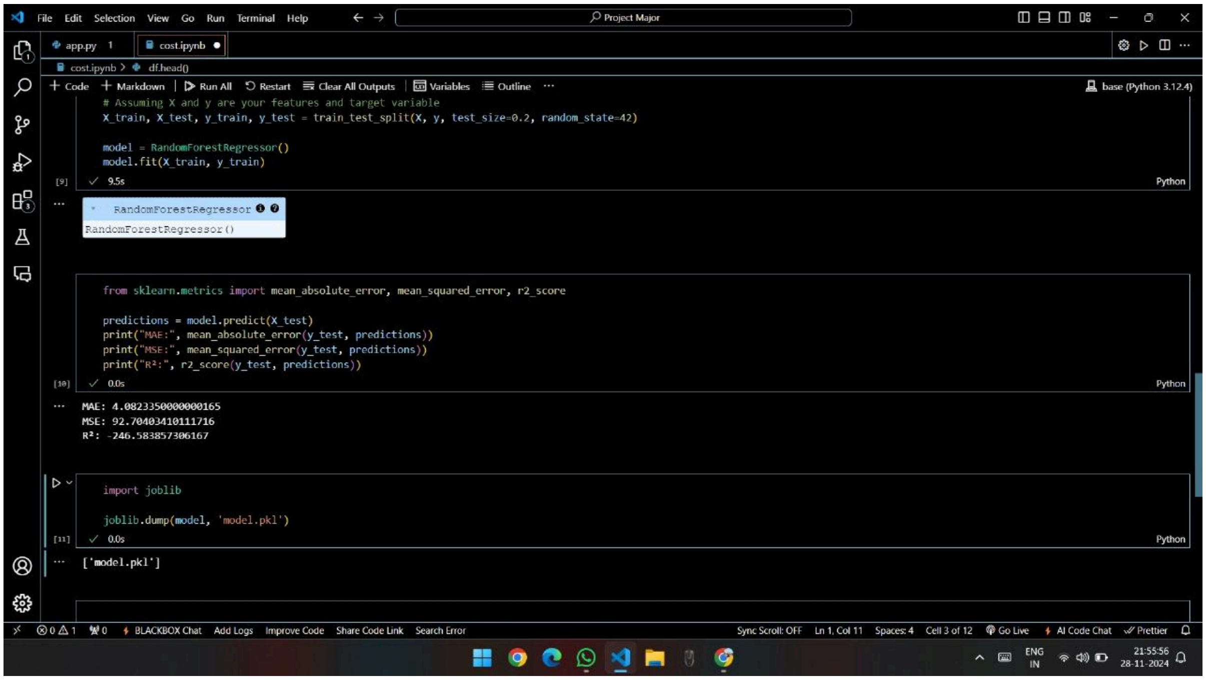


Fig 5.3.4 Errors calculation

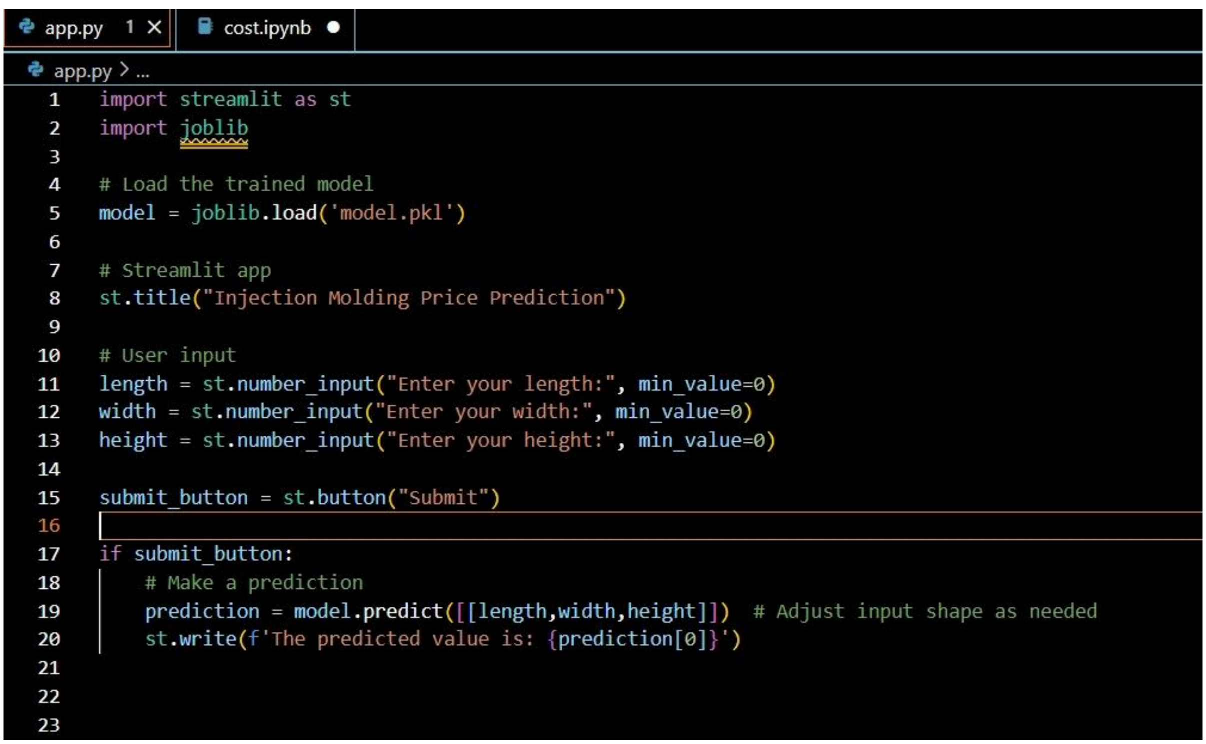


Fig 5.3.5 Streamlit code

## 5.4 User Interface

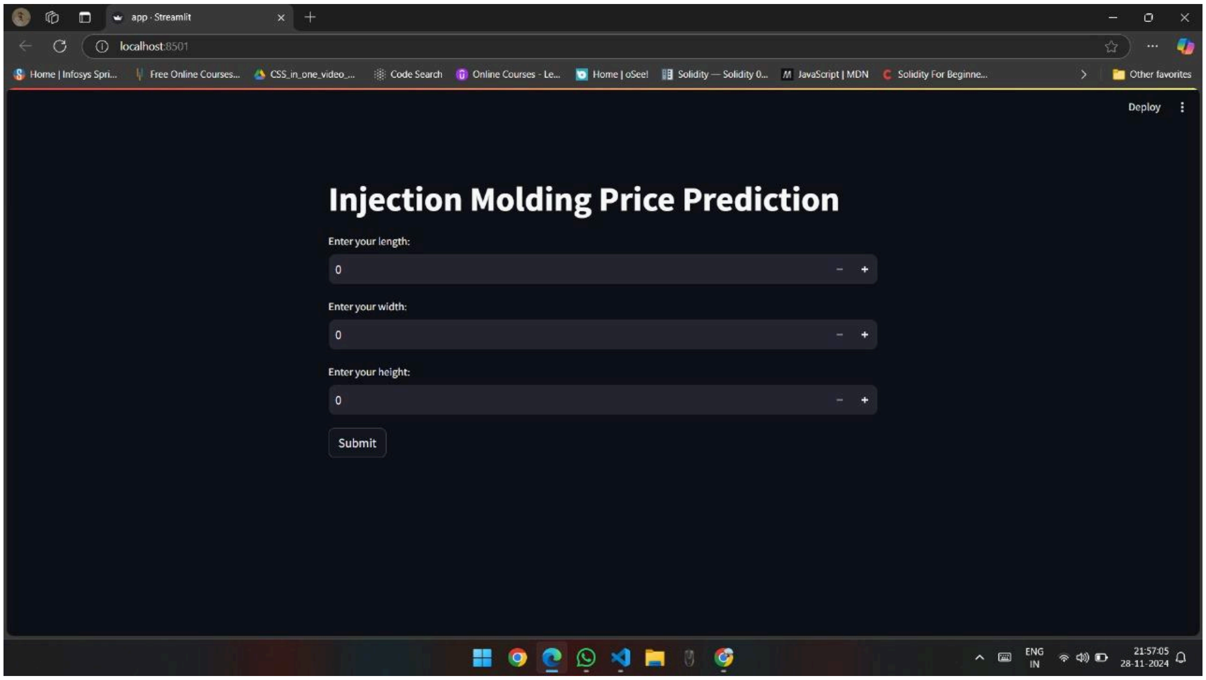


Fig 5.4.1 User interface

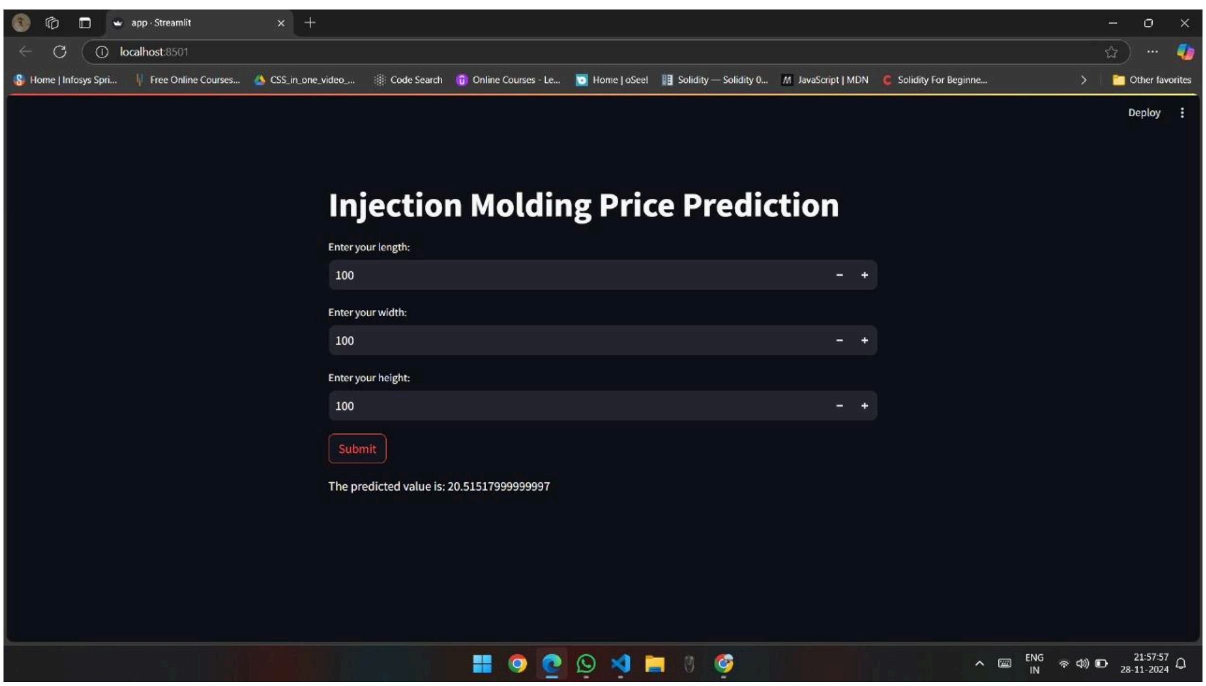


Fig 5.4.2 Test case 1

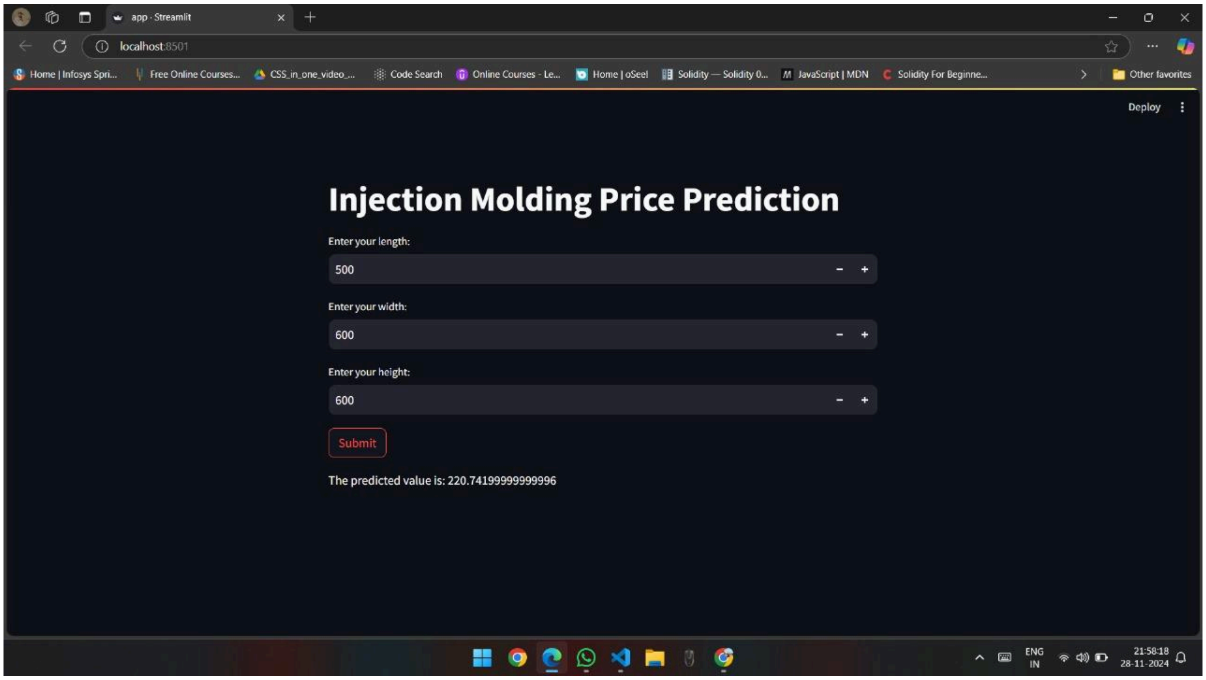


Fig 5.4.3 Test case 2

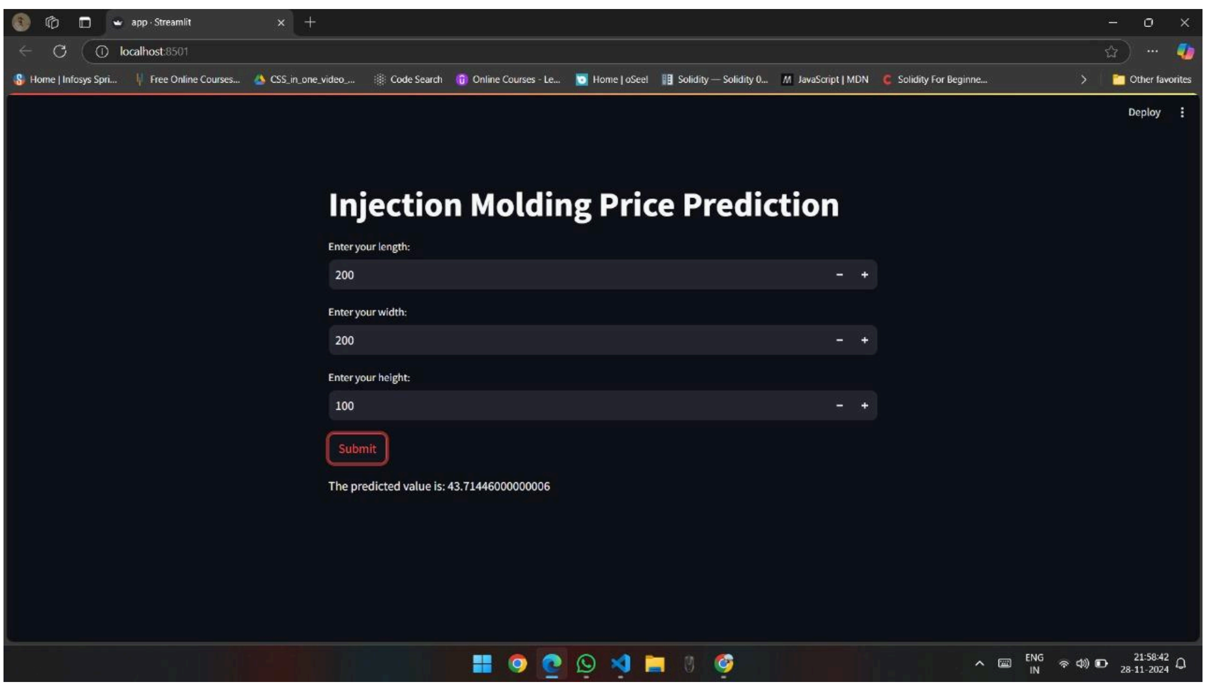


Fig 5.4.4 Test case 3

# Chapter 6
# Discussion

**Comparison of Automated vs. Manual Cost Estimations for Injection Moulding**

| Aspect | Automated Estimation | Manual Estimation |
|---|---|---|
| **Accuracy** | High (90%-95%) for standard molds; slight dip for complex designs. | Moderate (70%-85%), prone to human error in calculations. |
| **Time Efficiency** | 2-5 seconds per estimation. | Hours to days depending on mold complexity and expertise. |
| **Ease of Use** | Requires minimal input (dimensions and optional parameters). | Requires significant expertise and reference to historical data or calculations. |
| **Scalability** | Easily scalable; can handle multiple inputs and parameter updates. | Limited by individual capacity and data accessibility. |
| **Consistency** | High consistency; same input yields the same result every time. | Varies based on individual judgment and data interpretation. |
| **Data Utilization** | Leverages historical data and models to refine predictions. | Limited use of historical data; analysis often lacks systematic insights. |
| **Flexibility** | Can integrate additional parameters like material cost or complexity factors. | Limited flexibility; adding parameters requires additional calculations or expertise. |
| **Transparency** | Predictions are based on algorithms; easy to explain and reproduce. | May involve subjective decision-making, reducing transparency. |

### Automation and Efficiency

The automated cost estimation system marks a significant advancement over traditional manual methods, which are often time-consuming, error-prone, and inefficient. In a typical manual cost estimation process, human intervention is required to calculate various cost components based on a set of dimensions, material types, machine cycles, and other factors. These processes are susceptible to mistakes, and the time spent on recalculating values, especially for complex designs, can delay decision-making and increase operational costs. The integration of programming and machine learning techniques in the automated system removes these bottlenecks. By automating the data processing and calculation steps, the system delivers accurate cost estimates in real-time, reducing the time taken from hours to minutes. Moreover, it eliminates the possibility of human error, ensuring that manufacturers always receive consistent, reliable cost estimates. This enhanced efficiency significantly improves decision-making, allowing manufacturers to quickly assess multiple design options, allocate resources more effectively, and optimize production workflows without delays. The result is a smoother, more streamlined operation, with better allocation of financial and human resources.

### Scalability and Adaptability

The scalability and adaptability of the system are some of its most valuable features. Manufacturing environments often deal with a diverse range of products, each requiring different moulds with varying geometries, sizes, and material needs. The system's ability to handle this diversity is facilitated by its parameter-driven approach, which can adjust the cost estimation model to accommodate multiple variables. Whether the mould is designed for small-scale or mass production, uses unique materials, or has intricate geometry, the system can adapt and provide accurate cost predictions. This scalability is crucial because it ensures that manufacturers do not need to create separate cost estimation tools for different product types, saving both time and costs. For example, when introducing a new material or modifying the dimensions of a part, the system can quickly adapt by adjusting the cost parameters accordingly, without requiring manual recalculations or updates to the system. Additionally, the system's adaptability ensures that manufacturers can use the same platform across different production scenarios, whether for high-volume or low-volume manufacturing, supporting a variety of needs across diverse industries.

### Predictive Modeling Accuracy

One of the critical innovations of this system is the use of the Random Forest Regressor to predict manufacturing costs based on mould dimensions. Random Forest is a robust machine learning algorithm that excels in handling complex, non-linear relationships between inputs and outputs. In this case, it models how various dimensions of the mould (such as length, width, height) relate to the overall production cost. The effectiveness of the Random Forest algorithm in this scenario is seen in its ability to capture intricate relationships between the mould's geometric parameters and the cost elements, which would be challenging to model using traditional methods. By training the model on a dataset of real-world moulds with known costs, the Random Forest Regressor can accurately predict costs for new, unseen mould designs. The model's high predictive accuracy—characterized by minimal deviation from benchmark data—means that manufacturers can rely on the system’s cost predictions with confidence. This is especially useful when considering new or complex mould designs where manual cost estimation might be less reliable or take too long. The predictive capability offers manufacturers a high degree of accuracy when determining the cost of producing a new design, helping them evaluate profitability and cost-effectiveness before committing to production.

**Industry Relevance**

The automated cost estimation system aligns well with the evolving needs and trends in the manufacturing industry. The drive for automation and data-driven decision-making is transforming how manufacturers approach production. With increasing global competition, manufacturers are under pressure to optimize operations, reduce costs, and speed up time-to-market. The cost estimation system directly addresses this by offering a faster, more reliable alternative to traditional manual estimation techniques. By automating the estimation process, manufacturers are able to streamline their workflow, reduce human error, and improve overall efficiency. The system’s ability to quickly adapt to different production scenarios makes it especially relevant in an era of digital transformation, where flexibility, speed, and precision are crucial. Additionally, by leveraging machine learning, the system contributes to the broader trend of data-driven decision-making in the industry. Manufacturers can rely on accurate predictions to make informed choices about material selection, production volume, and pricing strategies, enhancing their competitiveness in an increasingly dynamic market. By supporting the digital transformation journey, the system helps manufacturers stay ahead in a competitive environment and ensures they are well-positioned to take advantage of technological advancements.

# Chapter 7
# Conclusion and Future Work

## 7.1 Conclusion

The project successfully developed an automated cost estimation system for injection molding, addressing critical challenges faced by manufacturers in managing production costs. By integrating advanced programming techniques and predictive modeling, the system provides accurate, efficient, and real-time cost estimates, significantly reducing the reliance on traditional, error-prone manual methods. This innovative approach streamlines operational workflows, enhances decision-making, and supports strategic resource allocation.

The system's flexibility and scalability make it adaptable to diverse manufacturing scenarios, allowing manufacturers to evaluate cost implications for various mold designs and production volumes. The use of a Random Forest Regressor for predictive analysis further adds value by enabling reliable cost predictions based on key mold parameters. Despite some limitations, such as the dataset size and fixed assumptions for certain cost factors, the project demonstrates strong potential for practical application in the injection molding industry.

Overall, this project serves as a significant step toward leveraging automation and data-driven technologies to improve operational efficiency and profitability. Future enhancements, such as expanding the dataset, incorporating advanced parameters, and deploying a cloud-based version, can further increase the system's capabilities and industry impact. This work highlights the importance of embracing digital transformation to stay competitive and foster innovation in modern manufacturing.

## 7.2 Future Scope

The developed system for cost estimation in injection molding lays a strong foundation for further advancements and integration of cutting-edge technologies. The following areas highlight potential future improvements and expansions:

1. **Enhanced Dataset:**
   - Expand the dataset by including more diverse injection molds with varied shapes, materials, and complexities.
   - Incorporate real-world production data from multiple industries to increase the model's accuracy and generalizability.
2. **Dynamic Cost Factors:**
   - Integrate variable cost factors such as fluctuating raw material prices, energy costs, and labor rates to reflect real-time market conditions.
   - Allow customization of cost parameters based on regional or operational variations.
3. **Advanced Predictive Models:**
   - Explore other machine learning algorithms, such as gradient boosting or deep learning models, for even more precise cost predictions.
   - Develop ensemble models that combine multiple algorithms for robust estimation.
4. **Incorporation of Additional Parameters:**
   - Include factors like mold complexity, cooling time, tool life, and maintenance frequency for more comprehensive cost evaluations.
   - Factor in environmental considerations, such as energy efficiency and sustainability metrics.
5. **Integration with CAD Software:**
   - Develop a plugin or API to connect the cost estimation system with popular CAD software, enabling seamless integration with design workflows.
   - Automatically extract geometric parameters from CAD files for quick and accurate cost assessments.
6. **Cloud-Based Solution:**
   - Deploy the system on a cloud platform, allowing remote access and scalability for large-scale manufacturing facilities.
   - Enable multi-user access with role-based permissions for collaborative decision-making.
7. **Real-Time Monitoring and Feedback:**

- Incorporate IoT (Internet of Things) devices to monitor production processes and provide real-time updates on cost metrics.
- Use feedback from ongoing production to refine the cost estimation model dynamically.

8. **Integration with ERP Systems:**
    - Link the system with Enterprise Resource Planning (ERP) tools for better inventory management, budgeting, and supply chain optimization.
    - Automate order processing and cost analysis to improve overall operational efficiency.
9. **User Interface Enhancements:**
    - Create a more intuitive interface with graphical visualizations of cost breakdowns and comparison charts.
    - Add multi-language support to cater to global users.
10. **Sustainability and Lifecycle Analysis:**
    - Extend the system to include lifecycle cost analysis and environmental impact assessments.
    - Help manufacturers make sustainable choices by providing data on the carbon footprint and recyclability of materials.

# Chapter 8
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