Quality Inspection Using Casting Product Image by Machine Learning Methods

Project Report
AN6001: AI & Big Data in Business

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1 Executive Summary

Casting is one of the many manufacturing processes which requires manual quality control inspection. It is a process where molten metal is poured into a mold to obtain a desired shape, which is then used as part of various products. Casting is a long process and traditionally, defect detection is done manually. This method has some drawbacks such as high labour cost, low efficiency and accuracy.

There are also business problems faced due to manual quality inspection which is tedious. Furthermore, the high inaccuracy in inspection leads to the manufacturing process in a company to become ineffective as the overall manufacturing process is affected. Thus, incurring high cost due to various reasons, such as failure costs, appraisal costs, preventive costs and labor costs. With large volume of castings done in a day, it is estimated that for every 1,000 tons of castings, 75 tons are defects. These defects needs to be properly identified, else they lead to a loss of profit.

In order to find a machine learning model to perform quality control inspection, we have sourced data and explored various models. With our sourced data, the best model is Neural Network, which has an accuracy of 99.7%.

By using our model to perform quality inspection, various business issues caused by manual inspection would be solved. This in turn leads to various operational and financial benefits. The operational benefits are reduction in inspection time, increase in inspection accuracy and high scalability. Whereas the financial benefits are increase in production rate, decrease in production cost, reduce cost caused by inspection errors and reduce labor costs. This in turn increase profitability and reduces overall cost. Our study explores these benefits in depth and also proposes a possible implementation plan for our model. We also briefly discuss other implementation opportunities, with various manufacturing lines, using Artificial Intelligence (AI) visual inspection.

Finally, the study will end of with the limitation of our model and future study ideas, which aims to further improve our results.

2 Introduction & Objective

2.1 Background

Manufacturing is the basic process to obtain a finished and usable product from raw materials. Majority of the items that we use in our daily life has undergone some form of manufacturing process. For an item to be usable and of high functioning quality, it needs to pass quality control. Quality control ensures that the products are free from defects and are able to perform the intended purpose successfully.

When a defective product passes quality control, it could result in a high cost for a company as the customer has to send back the defective product and this could result in a loss of trust with the customer. Furthermore, this would affect the reputation of the manufacturer and future customers might want to reconsider their manufacturer choice as well. This make quality control become a very crucial part of the manufacturing process where the final key decision, whether the final product is sold or scrapped, is made. Therefore, this decision effectively affects the total profits and total losses that a company makes.

Manufacturing has many individual processes which require quality inspection at the end of the individual process. This study focuses on one of those processes: casting. Casting is done by pouring liquid material into a target mould and allowing it to solidify [1]. During this process, casting defects, such as shrinkage defects, could occur. These defects are unwanted and could affect the performance of the final product. Hence, they need to be identified and removed from the manufacturing process line. Normally, companies use manual inspection to perform quality control for their casting products. This is a time-consuming process and is subjected to human accuracy, which is less than 100%. Thus, having high potential of product being rejected by customer, resulting in loss of money and trust for the company.

2.2 Study objective

By automating the quality checking process of casting, the accuracy of identifying defect products could be increased. Therefore, our study objective is to use machine learning to identify products which do not pass quality control.

Our study identifies and proposes a machine learning model to distinguish casting products which fail quality control inspection. Succeeding which, our study discusses business implementation and impacts of using machine learning for quality control of casting.

3 Literature Review

3.1 Process of casting in the company

Casting is a manufacturing process which produces desired-shape metal parts by pouring molten metal into a mold and solidifying and cooling it to room temperature. Casting is typically used to create intricate solid and hollow shapes, and cast products are found in a wide range of applications, including automotive components, aerospace parts, etc. It is an important method of manufacturing that helps to produce a different variety of products.

3.1.1 Casting Methods

There are different methods of casting such as gravity die casting, pressure die casting, investment casting, plaster casting, etc. The most common method is sand casting, which is often used for the production of large and simple products, such as roadside fences, iron pots and car engines parts. More than 60% of metal casting is done using the sand casting method.

3.1.2 Casting Materials

Most of the materials to be cast are metals (e.g. copper, iron, aluminum, tin, lead, etc.) that are originally solid but heated to liquid, while the materials of the casting mold can be sand, metal or even ceramics.

3.1.3 Casting Process

There are five main steps involved in the casting process:

1. Pattern Making
   The first step of this process is to select the shape of the mold and prepare the materials to use, which can be sand, wax, wood, metal, plastic, etc.
2. Core Making
   After making the pattern then comes the core making. The core is made when the casting requires some internal features like a hole. This step is optional as not all casting requires internal features.
3. Mold Making
   Following on, there is a requirement to create different types of molds for casting. Single-use mold can be made of sand, plaster or ceramic shell. Each of them has a different production method.

4. Pouring Process
   Now comes the most important step which is pouring. The first step of this method is to select the type of metal to be used for the casting purpose. Then the selected metal is melted and filtered to remove all the impurities and gases. And this molten metal is poured into the mold in such a way that the release of gases due to contact of the mold with the molten metal is the least.

5. Solidification Process
   Once the molten metal is cooled and solidified, the casting product is removed from the casting mold either by breaking the mold or by scrubbing using tools. After the ejection of the casting, it is cleaned to remove all the undesirable parts by cutting, sandblasting, tumbling, etc.

Figure 1 is an example of sand casting process which is split into detailed production steps: [2]

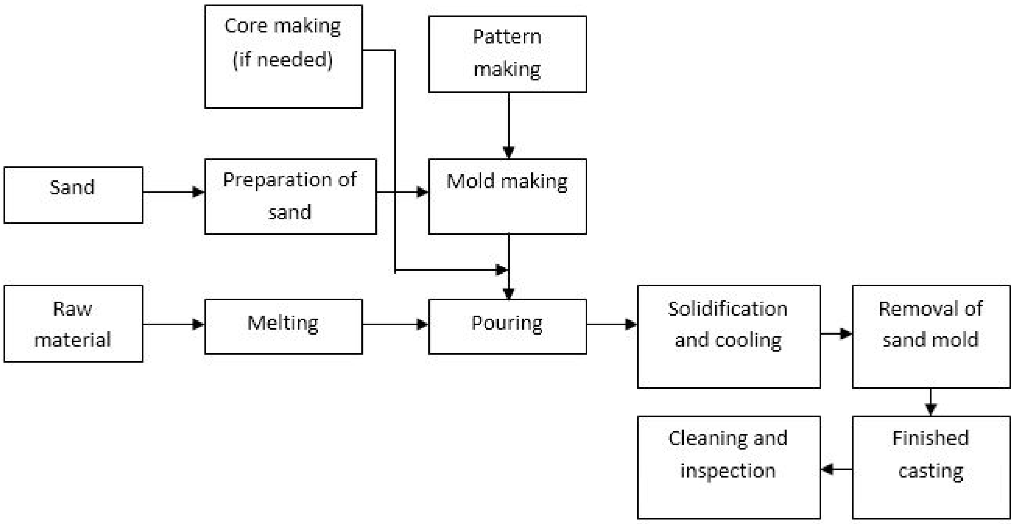

Figure 1: Sand Casting Process

As we can see from the graph, inspecting is the last step and forms part of the casting process. Casting defect is an undesired irregularity in a normal casting process. There are many types of defects in casting like blow holes, pinholes, shrinkage defects, mold material defects, pouring metal defects, metallurgical defects, etc. In order to eliminate such defective products, all industries have their quality inspection department. But the main problem is that this inspection process is carried out manually. It is a very time-consuming process and due to human accuracy, this is not 100% accurate.

3.2 Traditional Defect Detection

The defect detection plays an important role in casting manufacturing. Most traditional methods of casting defect detection are based on manual inspection, which is slow, inefficient and has poor robustness.

Traditionally, casting defect inspection is accomplished by human visual checking, which suffers from high labour cost and low efficiency. At present, most of the manufacturers are mainly using manual inspection for image defect detection of castings. The human visual checking is used to determine whether there are defects on the image of the castings, the type of defects, and whether it is to the extent that it needs to be overhauled or scrapped. The process has some drawbacks as follows: (1) high labour cost and low efficiency; (2) low accuracy owing to the individual competence and subjectivity of the tester; (3) a large number of inspection tasks and huge inspection intensity. [3]

According to research, visual inspection errors typically range from 20% to 30% (Drury & Fox, 1975). Some imperfections can be attributed to human error, while others are due to limitations of space. Certain errors can be reduced through training and practice, but cannot be completely removed. Therefore, it is urgent to find a method that makes the detection of casting defect efficient and accurate. [4]

3.3 Emerging Method of Quality Inspection

Machine learning-based method is getting more attention from the manufacturers who are looking to reduce costs and increase efficiency of quality inspection process. Compared with manual detection methods, the machine learning-based defect detection method has the following advantages: (1) lower manual labor and higher detection efficiency; (2) uniform and objective testing standards and higher stability; (3) less misdetections or missed detections when encountering a significant amount of the detection tasks. [3]

Specifically, the literature on the detection of defects in casting products contains a large number of methodologies, the majority of them revolve around deep learning models and in particular, convolutional neural network (CNN) algorithms. Recently, the resurgence of deep neural networks has achieved significant breakthroughs in the area of defect detection of products. [5]

Out of the various machine learning-based methods, visual inspection is one of the most commonly applied techniques which involves the analysis of products on the production line for the purpose of quality control. In AI-enabled visual quality inspection, reference examples are created by visual imaging of good and defective products from different perspectives that fuel the training of supervised learning algorithms. Machine learning abstracts from differences in illumination, imperfect surface orientation, or the presence of irregular background textures and focuses on defects only. Hence, machine learning enables the detection of defects that would only have become apparent at processing steps much further downstream using a conventional approach.

It has been shown that visual inspection results in the discovery of most hidden detects during production.

3.3.1 Significant Impact

The recent advancements in machine learning-based quality assurance promise productivity increases of up to 50%. For machine learning-powered visual inspection, detection accuracy of defects increases while simultaneously flexibility is enhanced and deployment times decrease. Improvements of up to 90% in defect detection as compared to human inspection are feasible using deep-learning-based systems. This reduces the costs associated with shipping bad products. Efficiency and speed are improved as the need for human input is lowered significantly. Generally, insights from AI-based quality testing can be used for root cause analysis to improve the overall production process. [6]

3.3.2 Wide Application

Given the availability of open-source AI environments and inexpensive hardware in terms of cameras and powerful computers, even small businesses are expected to increasingly rely on AI-based visual inspection. E.g., a Japanese cucumber farmer has used Google's open TensorFlow library to create a computer-vision-based tool for rating cucumber quality. [6]

While visual inspection is most often used in manufacturing for quality or defect assessment, in non-production environments, it can be used to determine whether the features indicative of a "target" are present and prevent potential negative impacts.

Among the many industries where visual inspection is required, there are several where visual inspection is considered to be high priority activity due to the potentially high cost of any errors that may arise via inspection such as injury, fatality, loss of expensive equipment, scrapped items, rework, or a loss of customers. Such fields where visual inspection is prioritized include nuclear weapons, nuclear power, airport baggage screening, aircraft maintenance, food industry, medicine and pharmaceuticals. [4]

As an example, visual inspection has been used in medical studies to diagnose the existence of certain diseases. Study shows that image inspection has been used in early phase detection of Coronavirus (COVID-19) by detecting from Computed Tomography (CT) chest images. The accuracy has achieved 99.68% in diagnosing COVID-19. [7]

4 Business Problem

4.1 Ineffectiveness

Casting defect is the main reason leading to low performance, short service life, scrap, and failure of castings. Casting defects can negatively impact the bottom line of a foundry. At the simplest level, they manifest as rework costs or casting scrap costs. However, in many cases, the casting defects may be discovered at the machining stage, at the assembly stage or during use of the component. The resultant value-added costs and warranty costs may sometimes be passed on to the foundry by their customer. These charges may be significantly more than the cost of the casting itself. Foundry personnel may not have the time to conduct a detailed casting defect analysis, determine root causes and implement effective corrective actions to prevent re-occurrence of these defects. So, we need an accurate and highly efficient model to predict and test.

4.2 High inaccuracy of manual inspection

Manual inspection requires the presence of a person, an inspector who performs assessment of the entity under question and passes judgement on it according to some training or previous knowledge. No equipment is required except the naked eye of the trained inspector.

According to research, visual inspection errors typically range from 20% to 30%. Some imperfections can be attributed to human error, while others are due to limitations of space. Certain errors can be reduced through training and practice but cannot be completely removed.

Visual inspection errors in manufacturing take one of two forms—missing an existing defect or incorrectly identifying a defect that does not exist (false positive). Misses tend to occur much more frequently than false alarms. Misses can lead to loss in quality, while false positives can cause unnecessary production costs and overall wastage.

4.3 High cost

We can capture, segregate, and track the costs of casting defects in four areas: failure costs, appraisal costs, preventive costs, and labor costs.

Failure Costs. Failure costs are those associated with correcting nonconforming material, including scrap, rework, repair, warranty actions, and others related to the correction of nonconformances.

Appraisal Costs. Appraisal costs are those related to the detection of defects. This cost category includes the costs of inspection, testing, and other measures used to separate good product from bad. Failure analysis and other activities focused on identifying underlying nonconformance causes should also be included in this category. Industrial experience shows that appraisal costs average around 15 percent of an organization's quality budget.

Preventive Costs. Preventive costs are those associated with activities designed to prevent defects. This is the area one would hope to have dominate an organization's quality budget. Such costs include participation in the design process to eliminate potential failure modes, process improvements designed to prevent production of nonconforming hardware, generation of Quality Function Deployment data.

Cost of labor. Manual inspection remains a costly venture due to the appointment of (multiple) trained individuals. Cost-wise, manual inspection operators may be earning a yearly salary of $50,000 to $60,000.

4.4 Quantize defect rate to lose of profit

Foundry castings are an essential part of daily life, and with over 90% of all manufactured items using a cast part, it's almost impossible to not interact with a metal casting.

Foundries still have thin margins and have to do everything they can to increase efficiency and decrease waste. One major problem is with casting defects where it's estimated that for every 1,000 tons of castings, 75 tons are defects that need to be melted down again. The exact rate of casting failure varies from foundry to foundry but can range from 3% to over 25%, which creates severe issues for the foundries.

Automated quality testing can be realized using AI. By employing advanced image recognition techniques for visual inspection and fault detection, productivity increases of up to 50% are possible. Specifically, AI-based visual inspection based on image recognition may increase defect detection rates by up to 90% as compared to human inspection.

5 Dataset Selection and Description

5.1 Statistical Features of Dataset Used

The data consist of 7,348 casting manufacturing product images. These photos are all top view of submersible pump impeller, which are the size of (300*300) pixels grey-scaled images. There are mainly two categories: (1) Defective (2) Non-detective. Data already split into two folders for training and testing.

Table 1: Overview of Dataset

Subfolder	Number of Defective images	Number of Non-defective images
Train	3,758	2,875
Test	453	262

5.2 Visual Features of Dataset

Casting defect is an undesired irregularity in a metal casting process. There are many types of defects in casting like blow holes, pinholes, burr, shrinkage defects, mould material defects, pouring metal defects, metallurgical defects, etc. In all images, augmentation has already been applied. Figure 2 shows example images of different types of casting defect.

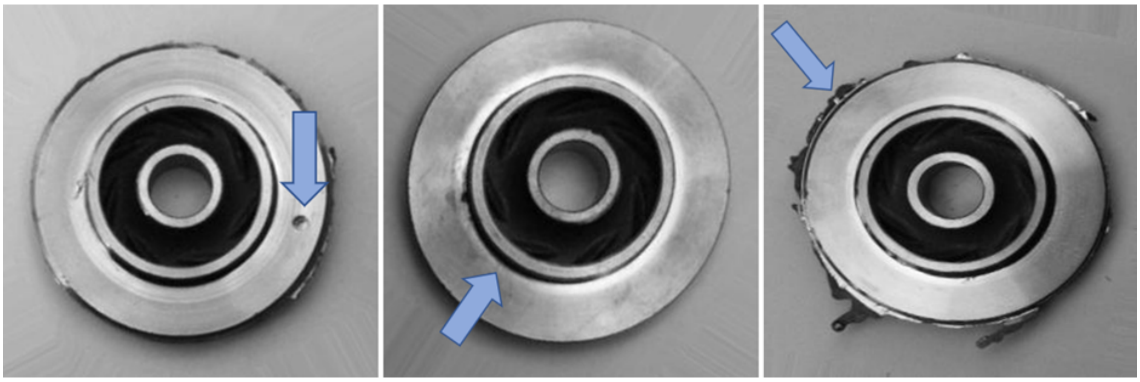

Figure 2: Different types of defects

When we compare defective products with non-defective ones, we can find that defective and intact areas have different visible differences in colours, lines, brightness, etc.. Figure 3 illustrates some differences between defective and non-defective products.

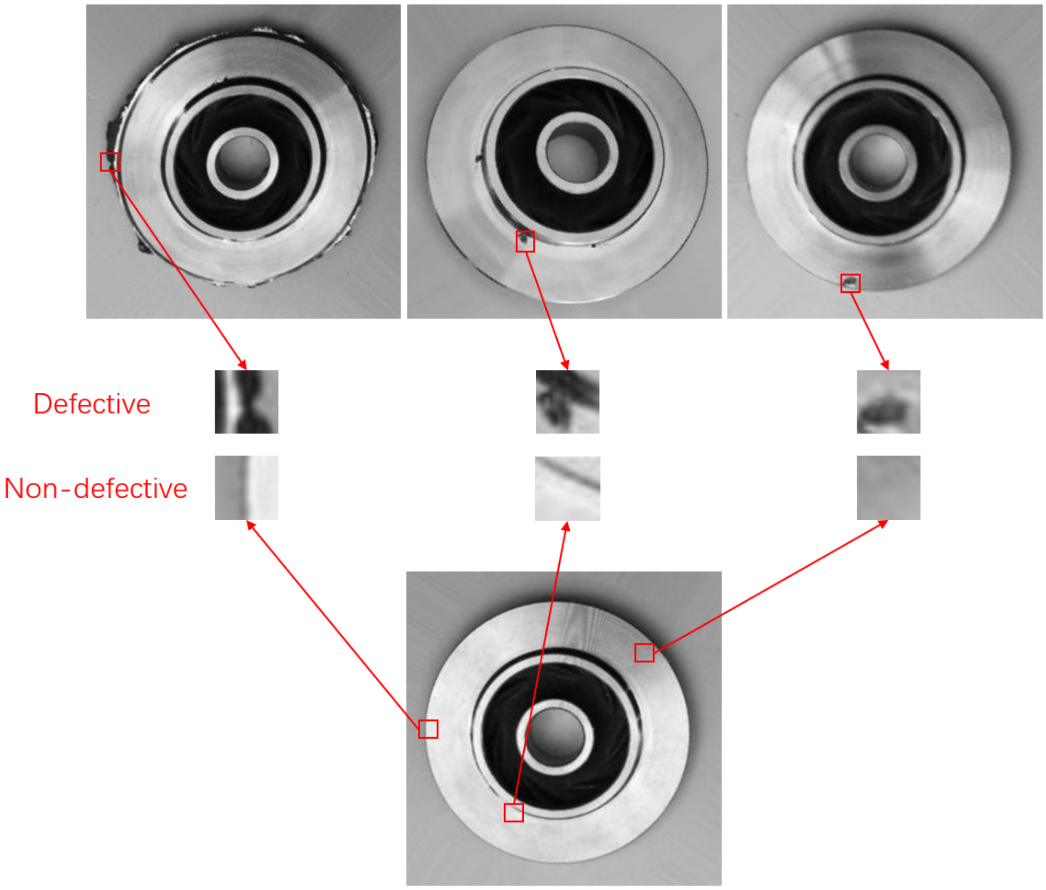

Figure 3: Comparison between defective and non-defective products

6 Methods

We choose Orange for data processing and model training & testing.Orange is an open-source machine learning and data visualization application, which enables us to build data analysis workflows visually, with a large, diverse toolbox.Graphic user interface allows us to focus on exploratory data analysis instead of coding, while clever defaults make fast prototyping of a data analysis workflow extremely easy. [8]

6.1 Image Embedding

Image Embedding reads images and uploads them to a remote server or evaluate them locally. Deep learning models are used to calculate a feature vector for each image. It returns an enhanced data table with additional columns (image descriptors).

In Orange, Image Embedding offers several embedders, each trained for a specific task. Images are sent to a server or they are evaluated locally on the user's computer, where vectors representations are computed. SqueezeNet embedder offers a fast evaluation on users computer which does not require an internet connection. Below are the image embedding models that Orange provides:

- SqueezeNet: Small and fast model for image recognition trained on ImageNet.
- Inception v3: Google's Inception v3 model trained on ImageNet.
- VGG-16: 16-layer image recognition model trained on ImageNet.
- VGG-19: 19-layer image recognition model trained on ImageNet.
- Painters: A model trained to predict painters from artwork images.
- DeepLoc: A model trained to analyze yeast cell images.

6.2 Machine Learning Models

6.2.1 Logistic Regression

Logistic Regression is the appropriate regression analysis to conduct when the dependent variable is dichotomous (binary). Logistic regression is used to describe data and to explain the relationship between one dependent binary variable and one or more nominal, ordinal, interval or ratio-level independent variables. [9]

6.2.2 Tree

Tree is a simple algorithm that splits the data into nodes by class purity (information gain for categorical and MSE for numeric target variable). It is a precursor to Random Forest. Tree in Orange is designed in-house and can handle both categorical and numeric datasets.

6.2.3 Gradient Boosting

Gradient Boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.

6.2.4 Random Forest

Random Forest builds a set of decision trees. Each tree is developed from a bootstrap sample from the training data. When developing individual trees, an arbitrary subset of attributes is drawn (hence the term "Random"), from which the best attribute for the split is selected. The final model is based on the majority vote from individually developed trees in the forest.

6.2.5 Neural Networks

Neural Networks are computing systems inspired by the biological neural networks that constitute animal brains. Neural Networks are based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain. Each connection, like the synapses in a biological brain, can transmit a signal to other neurons. An artificial neuron receives signals then processes them and can signal neurons connected to it. The "signal" at a connection is a real number, and the output of each neuron is computed by some non-linear function of the sum of its inputs. [10]

7 Result and Findings

7.1 Embedding Model Chosen

After trying all the Six embedding models provided by Orange, we chose InceptionV3 because of its highest accuracy [1]. InceptionV3 is Google's deep neural network for image recognition. It is trained on the ImageNet data set. The model we are using is available here. For the embedding, we use the activations of the penultimate layer of the model, which represents images with vectors. [11]

[1] Results of other 5 embedding models are provided in the Appendix

7.2 Experimental Results by Machine Learning

After embedding by InceptionV3, we trained five machine learning models (i.e. Logistic Regression, Tree, Gradient Boosting, Random Forest, Neural Network) respectively in Orange and had them tested using the testset we prepared. Figure 4 demonstrates the process of training and testing, Table 2 and Figure 5 shows the performance of all the machine learning models.

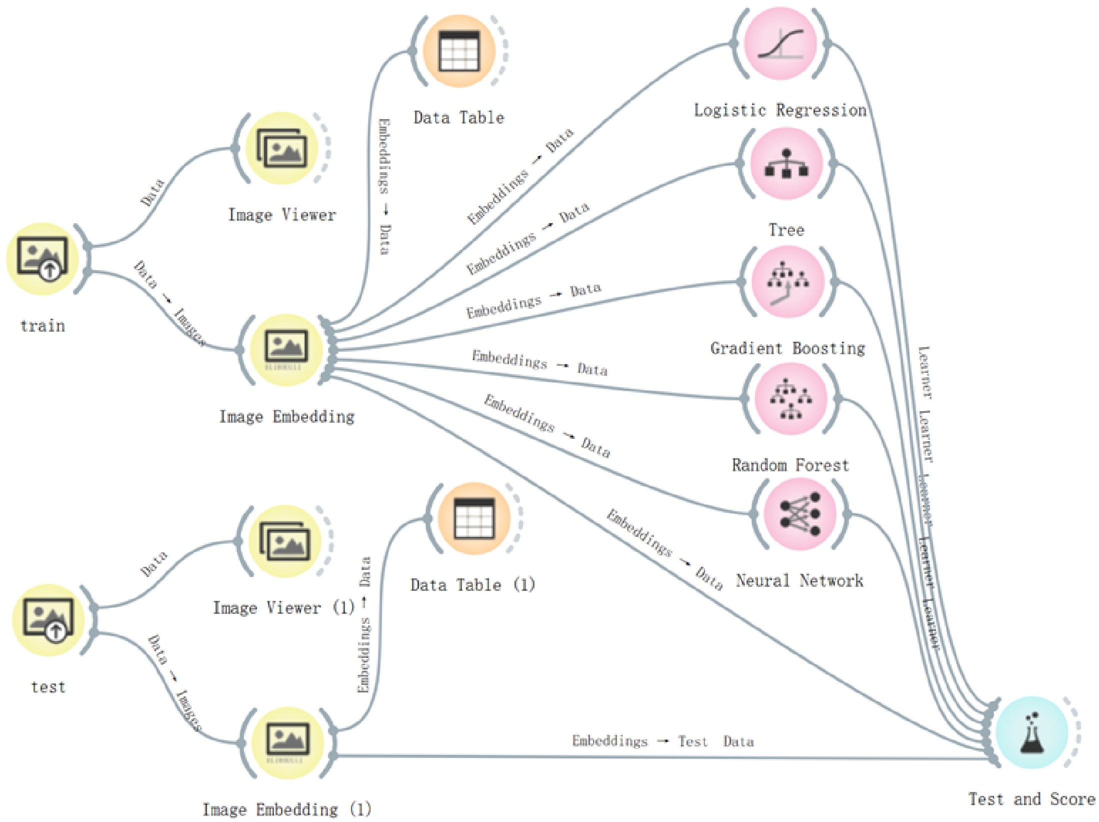

Figure 4: Process of training and testing in Orange

Table 2: Performance of five different machine learning models

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	1.000	0.997	0.997	0.997	0.997
Tree	0.905	0.929	0.928	0.928	0.929
Gradient Boosting	0.998	0.993	0.993	0.993	0.993
Random Forest	0.999	0.989	0.989	0.989	0.989
Neural Network	1.000	0.997	0.997	0.997	0.997

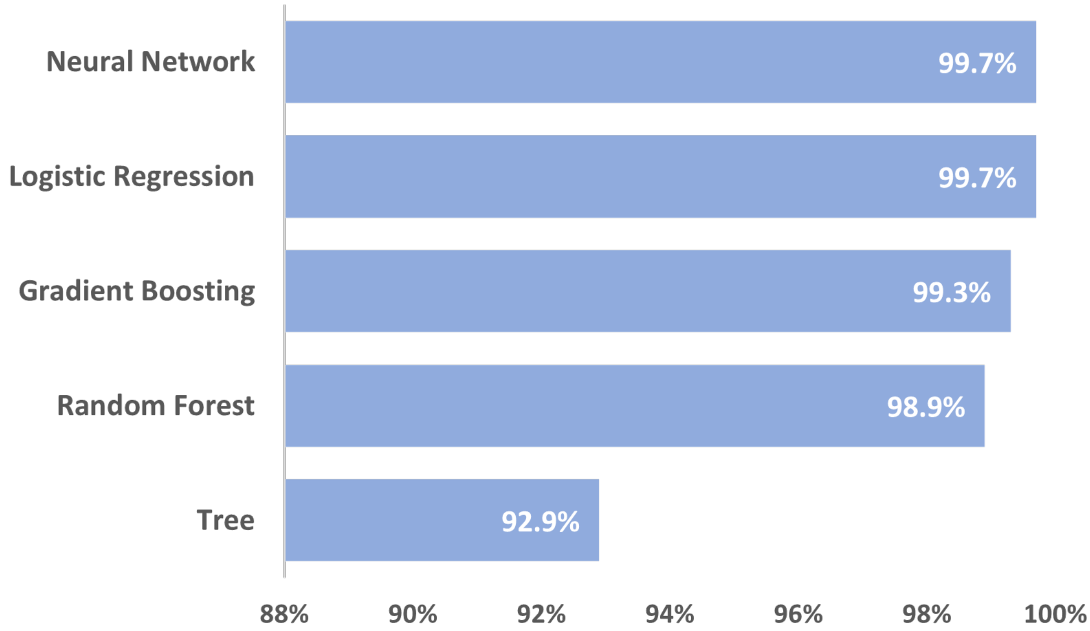

Figure 5: Comparison of classification accuracy

Based on the results we get from Orange, we decide to apply Neural Network as our machine learning model which has a higher classification accuracy, a better receiver-operating curve and a relatively more stable performance in future application.

8 Business Implications and Recommendation

8.1 Business Implications

Using artificial intelligence for visual inspection of casting product can solve business issues at once, such as bottleneck issue and high defect rate that are caused by manual inspection which is unreliable and expensive. The benefit of implementing AI can be translated into two major aspects which are operational implications and financial implications to the company.

8.1.1 Operational Implications

1. Reduce Inspection Time

   There are many types of defects in casting process, such as surface defects, cracks, gas evolution, slag or sand inclusions, misruns, cold shuts, and molding flaws. Since there are many types of defects, and a single product can have more than one type of defect, visual inspection using human eye will need longer time depending on the product dimension and number of defects type.

For this case, manual inspection approximately can take up around 10 seconds per product. However, machine learning only need 15.79 seconds to inspect on 715 images of products in the test data. This means AI visual inspection time is around 0.02 seconds per product. Assuming the time needed to capture the image is 5 seconds (depends on the speed of conveyor belt, image capturing devices, and software), the total AI inspection time per product is 5.02 seconds. This shows that AI-based solutions can decrease inspection time by up to 49.8 % compared to human inspection rates resulting in a much more efficient inspection process. Other than that, by lowering inspection time, bottleneck issues in the production floor can potentially be solved.

2. Increase Inspection Accuracy

   Manual inspection has two major limitations compared to AI. First, human vision is unreliable because it is incapable of making precise measurements and detect subtle surface defects. Second, manual inspection is inconsistent because the process is subjective to each inspector. This means every inspector can have different performance based on individual, environmental, task, organizational, and social factors. On top of that, inspectors' performance can decrease due to fatigue, unfocused or boredom. Compared to human vision, this study has developed a machine learning model to do visual inspection with 99.7 % accuracy. This accuracy is certainly higher than human vision and on top of that, machine is more reliable and consistent because it is independent to environment and cannot feel fatigue.

3. High scalability

   Manual inspection of new products requires hiring new inspectors or conducting additional training for inspectors to get used to the new dimension and defect types. This undoubtedly requires high cost and time. In contrast, visual inspection using machine learning can easily deployed to other casting products or to different production sites. Machine learning will only need to be trained in the early stages and can be utilized in long-term.

8.1.2 Financial Implications

1. Increase Production Rate and Decrease Production Cost

   A bottleneck is a congested area in a production system that causes the system to stop or move very slowly. The bottleneck's inefficiencies frequently result in lower production rate, higher production costs, presents large opportunity costs, and eventually delays in shipping goods to customers. By using machine learning that decrease inspection time, bottleneck can be eliminated. This can result in lower production and opportunity costs. On top of that, the production rate and capacity will be improved which will increase company's revenue. Therefore, by implementing machine learning in visual inspection, casting company can increase their profitability.

2. Reduce Cost Caused by Inspection Errors

There are two forms of visual inspection errors which are missing an existing defect (true negative) or mistakenly detect a defect that does not exist (false positive). False positive can cause unnecessary cost of rework and disposal. True negative can cause external failure costs which are expenses that the company must pay because the customers received defective products for example, warranty and return costs. In casting industry, true negative has a more fatal impact than false positive since customers highly put importance in defect rate and true negative can cause loss of trust and customers. By implementing machine learning with high accuracy, both errors will be compressed. Hence, it can reduce cost of rework, disposal and external failure costs, increase customers trust and overall will increase company's profitability.

3. Reduce Labor Cost

   Manual inspection is expensive because casting company needs to hire skilled employees. In fact, operators of manual inspections may earn around $40,000 annually [12]. Other than that, there is also training cost occurred when company has new products. In contrast, using AI can highly reduce cost of labor and training as it will no longer need manual inspection operators. The cost of implementing AI solutions is much cheaper which is around $20,000 [13]. Reducing labor costs will positively affect company's profitability.

8.2 Recommendation for Implementation

The production process of casting products is consisting of melting, die forming, grinding, drilling, polishing, and surface treating. In most of production process, there are usually 3 inspections that are carried out. The first inspection is carried out after die forming, the second is carried out after grinding and drilling, and the third is carried out after polishing and surface treating. As shown on the figure 6, this project focused on implementing AI visual inspection on the third inspection which will inspect quality of finished goods before it is sent into the warehouse. The third inspection will have the highest impact by utilizing AI because it is the final inspection, but of course the first and second inspection can also utilize AI which can be explored for future study.

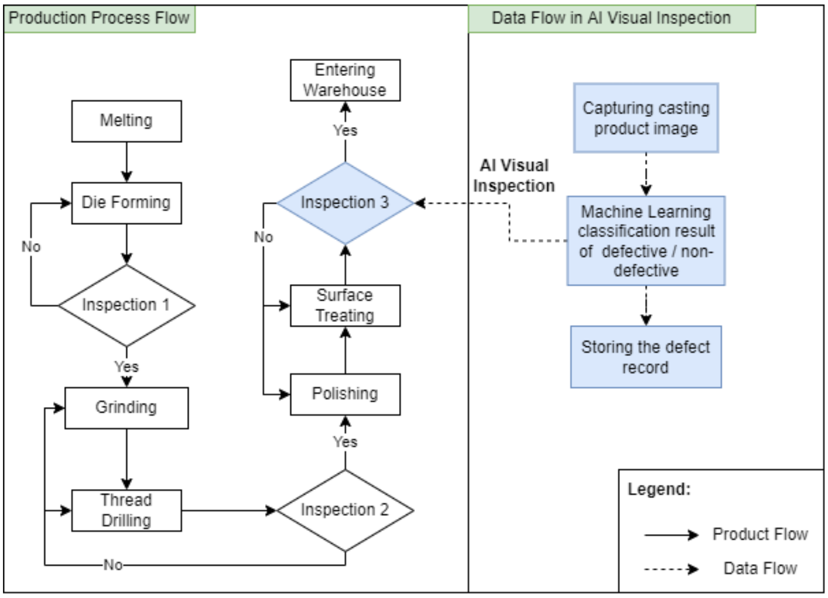

Figure 6: Production Process and Data Flow in Implementing AI Visual Inspection

The first step in AI visual inspection is capturing casting product image. The optical system which consists of a camera and specially tuned illumination source is recommended to be used. The optical system will capture the product, which are then processed and analyzed by the software. Devices needed for the optical system are camera, CPU / GPU for real-time results, and light alert (green for non-defective, red for defective products). Figure 7 illustrates how optical system works. The optical system will be placed in the conveyor belt, where each product will go in a black box with light and camera inside of it. This setting is crucial to be built so image can be captured in stable lighting condition. After the image is captured, machine learning can then process the image and classifies it as defect or non-defective. The defect data will be recorded in either the local server or cloud streaming server.

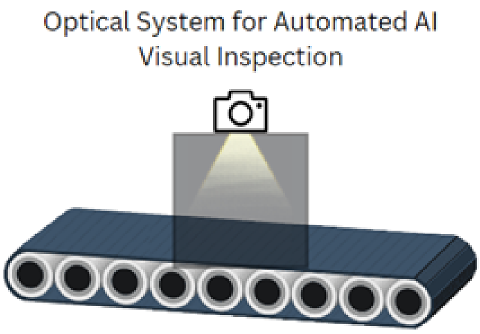

Figure 7: Optical System Illustration

8.3 Other Implementation Opportunities

Other implementation opportunity in using AI visual inspection is just not limited to detect defects but also conducts root cause analysts, predictive maintenance, and production optimization. By using the defect record, AI can track their sequence or any pattern in the defect data and give warning to employees. By integrating the defect record and machine maintenance data (sounds or vibrations of machines), AI-driven root-cause analysis can minimize future defects by identifying the production chain part that needs modification and give maintenance worker a predicted maintenance and its schedule. This can reduce machine downtime, inspection costs, scrap rates, and annual maintenance costs. This implementation opportunity can also be utilized in other industries other than casting industry. Other industries that utilize visual inspection is shown in Table 3 [14]

Table 3: AI Visual Inspection Implementation Opportunities

Industry	Targets	Defects
Automobile	Material parts Resin parts Fabric	Scratch Crack Dirt Dent Burr / chip
Electronic	PCB Electronic parts Electrical component Panel	Scratch Crack Burr / chip
Building Materials	Wood board Sash Metal fitting Tile	Scratch Crack Dirt Dent Surface Pattern

Nonferrous Metals	Wire, cable Aluminium Stainless Steel	Scratch Crack Dirt Dent
Raw Materials	Chemical fiber Rubber Glass Paper, pulp	Scratch Crack Dirt Dent
Food	Processed food Beverage	Foreign object Wrong print Leak
Medical	Medicine	Foreign object Wrong print Crack
Others	Material parts Resin parts	Defect classification Shape check

9 Limitations

Despite having high prediction accuracy, we do note that there are some limitations to using machine learning to perform quality control.

Quality control cannot be performed by machine learning to identify internal defects. Since the images are of the exterior of the castings, defects are clearly visible on the image. However, internal defects, such as air bubbles in the casting, are not so clearly visible. Hence, our model will not be able to identify products with internal defects.

Our model will not be able to assess the casting on its functionality. Some castings may not have any defects however, they may fail to perform their function due to inaccurate dimensions. Resulting in the product being unusable even though it would pass our model's quality check.

10 Conclusion and Future Study

10.1 Conclusion

In this project, we have developed a machine learning model using Neural Network with Inception v3 Embedders that can successfully applied in inspecting casting product. The accuracy of the model is really high which is 99.7%. The operational implications by utilizing AI visual inspection are reducing inspection, increasing inspection accuracy, and higher scalability. These operational implications can be translated into financial benefits which are increase in production rate, and decrease in production cost, cost caused by inspection errors, and labor cost. This leads to higher revenue, lower overall costs, and higher profit. The company can easily implement this by using our implementation plan that utilizes simple optical system or utilize AI for broader purposes to conduct root cause analysts, predictive maintenance, and production optimization.

10.2 Recommendation for Future Study

The model used in this study achieve 99.7% accuracy. However, we realized that in casting industry, customers usually expect 0.05% defects for machined parts. To maximize the strength of visual inspection and accuracy up to 100%, we recommend that implementation of AI visual inspection is combined with human manual inspection. In this case, as shown in Figure 8 the result of machine learning classification can be defect, non-defective, and not sure. The "not sure" category is result of classification with high uncertainty and will be further inspected manually. This can result in inspection system with 100% accuracy with low additional labor cost.

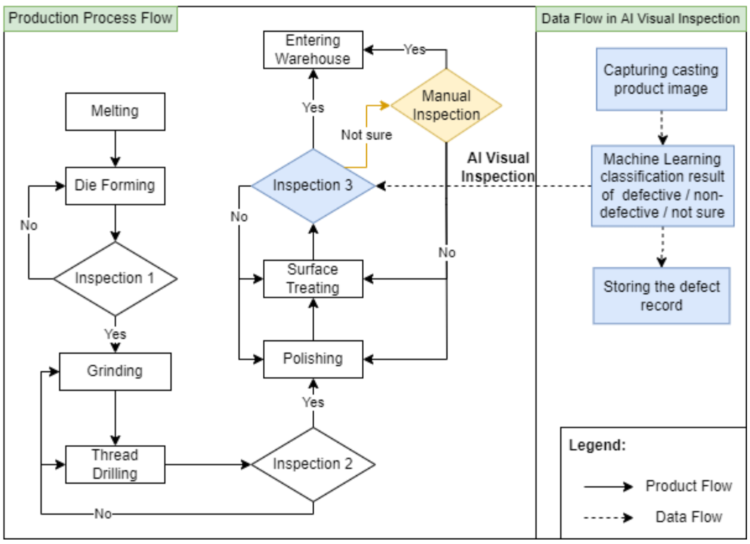

Figure 8: Production Process and Data Flow when Combining AI Visual Inspection and Manual Inspection

Future study can tackle the development of machine learning model that classify based on uncertain predictions. Possible machine learning model to be explored is ensemble of convolutional neural networks. Other than that, future study can also explore the utilization of 3D vision sensor and employ deep learning models to not only detect surface defect, but can also detect structure, dimension, and density of casting products.

11 Appendix

11.1 Other Embedding Models and Their Results

11.1.1 SqueezeNet

SqueezeNet is a deep model for image recognition that achieves AlexNet-level accuracy on ImageNet with 50x fewer parameters. The model is trained on the ImageNet dataset. We re-implemented the SqueezeNet by using weights from the author's pretrained model. We use activations from pre-softmax (flatten10) layer as an embedding.

Table 4: Performance of five different machine learning models (SqueezeNet)

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	0.998	0.986	0.986	0.986	0.986
Tree	0.884	0.916	0.916	0.916	0.916
Gradient Boosting	0.999	0.985	0.985	0.985	0.985
Random Forest	0.996	0.976	0.976	0.976	0.976
Neural Network	1.000	0.996	0.996	0.996	0.996

11.1.2 VGG-16 & VGG-19

VGG16 and VGG19 are deep neural networks for image recognition proposed by Visual Geometry Group from the University of Oxford. They are trained on the ImageNet data set. We use a community implementation of networks with original weights. As an embedding, we use activations of the penultimate layer fc7.

Table 5: Performance of five different machine learning models (VGG-16)

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	1.000	0.990	0.990	0.990	0.990
Tree	0.953	0.944	0.944	0.946	0.944
Gradient Boosting	1.000	0.994	0.994	0.994	0.994
Random Forest	0.999	0.993	0.993	0.993	0.993
Neural Network	1.000	0.992	0.992	0.992	0.992

Table 6: Performance of five different machine learning models (VGG-19)

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	0.996	0.986	0.986	0.986	0.986
Tree	0.929	0.938	0.938	0.938	0.938
Gradient Boosting	0.999	0.987	0.987	0.988	0.987
Random Forest	0.999	0.982	0.982	0.982	0.982
Neural Network	1.000	0.992	0.992	0.992	0.992

11.1.3 Painters

Painters is an embedder that was trained on 79,433 images of paintings by 1,584 painters and won Kaggle's Painter by Numbers competition. Activations of the penultimate layer of the network are used as an embedding.

Table 7: Performance of five different machine learning models (Painters)

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	1.000	0.997	0.997	0.997	0.997
Tree	0.953	0.959	0.960	0.960	0.959
Gradient Boosting	1.000	0.997	0.997	0.997	0.997
Random Forest	0.998	0.997	0.997	0.997	0.997
Neural Network	1.000	0.993	0.993	0.993	0.993

11.1.4 DeepLoc

DeepLoc is a convolutional network trained on 21,882 images of single cells that were manually assigned to one of 15 localization compartments. We use the pre-trained network proposed by authors. The embeddings are activations of penultimate layer fc_2

Table 8: Performance of five different machine learning models (DeepLoc)

Model	AUC	CA	F1	Precision	Recall
Logistic Regression	0.984	0.937	0.937	0.939	0.937
Tree	0.942	0.950	0.950	0.950	0.950
Gradient Boosting	0.992	0.959	0.960	0.961	0.959
Random Forest	0.998	0.973	0.974	0.974	0.973
Neural Network	0.998	0.989	0.989	0.989	0.989

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