Multisided Quality Inspection in Smart Manufacturing Systems

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Multisided Quality Inspection in Smart Manufacturing Systems

Milica Babic

Thesis submitted to the
Benjamin M. Statler College of Engineering and Mineral Resources at West Virginia University

in partial fulfillment of the requirements for the degree of
Master of Science in Industrial and Management Systems Engineering

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Keywords: Smart Manufacturing, Industry 4.0, Quality 4.0, Machine Learning, Supervised ML, Classification, CNN, Geometrical Optics

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ABSTRACT

Multisided Quality Inspection in Smart Manufacturing Systems

Milica Babic

As technology advances so does its adoption in industry and our everyday lives. We use technology to better our daily tasks whether at home or in the workplace. In the workplace there are many benefits of implementing new technologies to improve processes and products while at the same time being cautious about associated costs. Costs associated with incorporating new digital technologies include but are not limited to hardware and software, system integration, testing, and employee training. Now that we have entered the era of the Fourth Industrial Revolution, there are many opportunities for improvements in manufacturing that involve Smart Digital Technologies.

Quality Inspection (QI) is a common process in the manufacturing industry. This process serves to identify and locate defects based on preassigned product features. It can be used to find defect causes during the manufacturing process. QI is an established process that is often conducted manually. However, with the opportunity afforded by core Industry 4.0 technologies like Machine Learning (ML), the QI process is increasingly automated. A literature review on the topic of Image Based QI shows that today the designs of fixed single camera based QI systems inspect only one side of a product. In case multiple sides of a product need to be inspected, more datapoints are acquired via either multiple cameras or moving the camera system which affects the length of process, task complexity, cost, and data storage. This thesis explores the application of a mirror system in the design of a QI station to overcome this current limitation and potentially lower the number of processing tasks and increase the inspection ability of one automated station. The images acquired for the QI experiment present a simultaneous, multi-side (five sides) view of a product with similar accuracy.

The experiment is set up with three major parts: 1) a physical setup of a mirror-enhanced camera system for part QI; 2) a set of test parts with two types of simulated common surface defects (additional material and scratches) to create the data set for analysis, and 3) a Python-based ML model to analyze the data set and evaluate the system’s ability to correctly identify errors on multiple sides of the specimens. The results show that the setup successfully identified the majority of surface errors on all sides of the part with an accuracy of at least 85% when applying an Artificial Neural Network based supervised ML classification approach. This supports the hypothesis that mirror enhanced images can be used to support the QI process by enabling multi-sided inspection using a stationary single-camera setup in combination with supervised ML classification.
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1. Introduction

Industrial Engineering focuses on continuous improvement of processes specifically in manufacturing [1]. Improvement decisions in industrial design, construction, and maintenance of facilities usually depend on health and safety, quality, law, and profit. The proposed setup design in this paper focuses on time, quality, and data storage improvement. Utilization of automation technology in manufacturing processes is rising. The Industrial Automation Market is growing rapidly over a 6% CAGR at value of $149 billion (2015-2022) and forecasted 8.4% CAGR & $298.7 billion in value (2020-2030) according to the Market Research Future report [2]. Additionally, there is an increase in research in Image Based QI with 87.76% increase in the 2016-2020 timeframe, and research on automation of material QI in comparison to human intervention makes 32% of topics [3]. Indicating that automation implementation in industry and image QI automation demand are correlated. There are many types of Inspection process types. Examples are Image Based systems which use images as datapoints for quality analysis and defect detection purposes [3]. The following subsections cover the motivation and research gap which led to this work’s design idea and the investigation that supports it.

1.1 Motivation Aim and Scope of the Dissertation

After conducting a literature review on the topic of Image Based QI in Smart Manufacturing Systems [3], it was found that all reviewed papers that worked with single or multiple camera setups captured individual side images of their inspected product and used it as datapoints. This research focuses on introducing the Multisided QI by implementing mirrors and using Geometrical Optics laws to improve the camera acquisition based processes.

This work assesses the impact of QI setup design improvement using Geometrical Optics through ML. Many Image Based QI works used single camera setups [3]. The addition of mirrors has a potential of impacting the amount of image orientations collected, the quality of the data, system processing time and more. Improving a QI process can lead to faster response time after defect detection which leads to
possible improvements on health and safety, quality, and profitability of the manufacturing process and product.

1.2 Research Questions

When assessing products using Image Based Quality Control, data collected is initially in the form of images which are then analyzed through the ML process. These images can be of one side of the product not addressing if other sides have defects, multiple individually taken sides with one camera which is time consuming, or with multiple cameras which results in high costs. High costs, time consumption and complexity of current QI systems which allow multisided inspection are likely reasons why 86% of Image Based QI research papers focus on a single side inspection [3][4]. Mirrors have been used in QI processes in industry to help operators locate defects [5] but upon conduction a literature review, no mirrors were used for designing an automated multisided Image Based QI process [3]. The research gap will be covered in more depth in the second section. This work’s proposed inclusion of mirrors would capture five sides of a product (excluding the chosen bottom). The possible impacts in this area would be more data inclusion through a single photo which lowers the number of images needed along with the data space they use which reduces the multisided inspection QI time and cost, and the quality of the data could be impacted due to image distortion caused by the mirror angle and placement. The system is designed to be automated and alarms an operator only when a defect is found thus lowering the operator time for this process. Due to the increase of information in a single image, the data analysis time through ML could be impacted. To assess this, the following questions must be answered:

1. Has the inclusion of mirrors been researched within the works of Image Based Quality Inspection?

2. Can the proposed system identify defects on four sides of the part in the distorted mirror images? What is the acceptance rate gained using the Confusion Matrix?

3. Is there a difference in acceptance rate of the four sides and top side?
1.3 Organization of the Thesis

This thesis includes six sections followed by acknowledgements and reference sections in the end. The first section provides a general introduction into the topic of Image Based QI, motivation and scope of the study, and research questions and objectives that was discussed in the following sections.

The second section provides a more detailed background of Image Based QI and identifies the research gap based on a literature review published [3]. The first two subsections cover the Fourth Industrial Revolution, Smart Manufacturing, and ML which contribute to Quality 4.0 (Q4.0). The next subsection showcases the increase of Image Based QI in research after Industry 4.0 was officially introduced. The last part of this section covers a physics topic of Geometrical Optics as it was later used with ML to enhance an Image Based quality control process.

The third section explains the steps taken to complete the research, from conducting a literature review, explaining why the qualitative research method was chosen, to gathering results and drawing conclusions.

The fourth section covers more in depth how the experiment was conducted. The sub-sections introduce the environment within which the experiment was conducted including the physical setup, workpieces which are the products to be inspected, software and data acquisition, and ML model evaluation respectively.

The fifth section shows the collected results from the ML models, the evaluations of these models (Confusion Matrix) and discusses the overall success and issues of this QI design.

The final chapter concludes findings, discusses limitations of the work, and proposes potential scopes for future work to expand upon this specific case study.
1. Literature Review

This Thesis includes the following publications. These publications include two publications in refereed conference publications in an international and a national conference. Table 2.0.1 mentions the publication’s reference, the corresponding Conference and status with estimated submission time. Table 2.0.2 shows each publication’s contribution to this Thesis.

Table 2.0.1 - Publication and their publication status.

<table>
<thead>
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<th>No.</th>
<th>Reference</th>
<th>Conference</th>
<th>Status</th>
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<tbody>
<tr>
<td>2</td>
<td>M. Babic, A Billey, T. Wuest, and M. Nager (2022), “Status Quo of Smart Manufacturing Curricula offered by ABET accredited Industrial Engineering programs in the US”</td>
<td>North American Manufacturing Research Conference (NAMRC) 50</td>
<td>Published</td>
</tr>
</tbody>
</table>
Table 2.0.2 - Contribution of Publications to Thesis.

<table>
<thead>
<tr>
<th>Publication</th>
<th>Contribution</th>
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<tbody>
<tr>
<td>1</td>
<td>Addresses the QI design topic knowledge gaps, and supports the assumption that there is a lack of research on the topic of QI design in regards to inclusion of mirrors to improve the single camera based design.</td>
</tr>
<tr>
<td>2</td>
<td>Researches the spread of Smart Manufacturing knowledge and skill set in ABET accredited universities. The results indicate that there is a shortage of skilled workers and workforce preparation in this area. Main Smart Technology (ST) enablers included in Smart Manufacturing are Artificial Intelligence and ML. Supporting that manufacturing should include simpler ST aided processes which would require less training and/or prior knowledge.</td>
</tr>
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2.1 Smart Manufacturing

Smart Manufacturing or Industry 4.0 is a large field that was made public in 2011[3]. Smart Manufacturing technology are enablers of the 4th Industrial Revolution [6] and following CESMII’s definition: “Smart Manufacturing is the information-driven, event-driven, efficient and collaborative orchestration of business, physical and digital processes within plants, factories and across the entire value chain” [7]. A crucial component of Industry 4.0 is its ST which uses Big Data Analysis, ML, and Artificial Intelligence to provide cognitive awareness to systems [8]. Manufacturing Data Analytics is a field affected by ST innovation such as ML systems [6]. The Fourth industrial revolution uses data for decision making and automation based to improve productivity, precision, performance, and energy consumption [9].
2.2 Machine Learning and Quality 4.0

One of Industry 4.0 enabling technologies is Machine Learning. In ML, models are created to help computer systems train by analyzing data to make predictions which lead towards autonomous decision making [10]. These systems along with other ST are used to better processes, such as QI which leads to Q4.0 [11]. Q4.0 is an extension of Industry 4.0 and is not a replacement to traditional quality methods which enable error detection and improve decision making. With mass production, customization, and digitalization comes the problem of dealing with large amounts of data, and traditional methods result in delays in execution of corrective actions [5][11]. Q4.0’s purpose is to build upon existing methods by increasing reliability of production output by maximizing overall equipment effectiveness and minimizing costs of maintenance, scrap material etc. Based on research done by LNS research, 37% of companies surveyed report that poor metrics are a top roadblock towards their quality objectives. ML improves traditional quality methods by increasing the ability of analyzing large amounts of data (Big Data) and training the system to determine correlations based on data trends. The results from this process are often reduced costs and improved workflows [13].

2.3 Image Based Quality Inspection

There are many types of QI processes. In the field of manufacturing, visual quality detection of products is one of the more important issues and application of ML is more commonly related to enhancing visual QI [14]. [15] and [16] express the advantages of ML inclusion in visual inspection with enhancement in production, efficiency, product quality, and cost reduction. After conducting a literature review on the topic of Image Based QI in Smart Manufacturing Systems, a pie chart was constructed which represents the distribution of this topic’s focus areas (Fig.2.3.1) [3]
Fig. 2.3.1 – Pie Chart: Representation of paper focus area distribution [3]

The results presented in the figure above indicate that most research focuses on evaluation of current systems and improvement proposals. The large increase in publications on this topic (Fig. 2.3.2) indicates a recent increase in the need for improvement of QI processes which in turn supports the indication that one of the most important issues in the manufacturing field is Visual QI of products [3][14]. QI can help identify defect patterns which can help prevent future defect repetition [17]. Upon further research into the topic of Image Based QI, the review showcases a high interest in single camera based systems (86%) likely due to high camera costs which increase the QI time if the process inspects multiple sides. Additionally, 86% of papers inspected only one side of the product (single or multi-camera) which could result in misidentifying defective products.

Fig. 2.3.2 - Histogram: number of publications related to Image Based Quality Control research (timeframe 1978-2020) [3]
2.4 Geometrical Optics

Mirrors have been used by operators during manual QI to aid by showing where their eyes cannot reach [5]. Geometrical Optics is a scientific area which studies passage of light through lens, prisms, mirrors, etc. by representing light as rays [18]. Geometrical optics is important for this research because it studies light reflection in this case specifically mirror reflection laws are needed. As we utilize mirrors, there are two main areas that need to be addressed: mirror type and placement. The position of a mirror is important as only certain positions can reflect an image of an entire object onto another object. This is addressed by the laws of reflection which states that the angle of reflection $\theta_r$ equals the angle of incidence $\theta_i$ relative to the perpendicular point of the mirror surface (Fig.2.4.1(A)). A mirror reflects rays in only one direction which means that the camera can only capture the reflection at a certain angle (Fig.2.4.1(B)) [19].

![Fig.2.4.1 – (A) The law of reflection](image1) ![Fig.2.4.1 – (B) Mirror reflection](image2)

2.5 Addressing the Research Gap

Based on the literature review and additional research, lowering costs, design/process complexity and other factors might influence a company’s decision to implement Image Based QI systems[3][4]. More research focuses on one sided in comparison to Multisided QI (86%), and single camera based in comparison to use of multiple camera QI (86%) which creates a problem of either missing defects on other sides of the product or consuming more time and data storage for constructing a 3D model [3]. Perfecting, automating and including ML into the QI process can lead to defect pattern detection which can help find and solve the manufacturing issue that caused the defects [17]. This could save on costs
from returns, scrap, equipment failure etc. There was no research found that addresses inclusion of mirrors and Geometrical Optics in an Image Based QI [3]. This paper proposes a design which could give QI the capability of inspecting multiple sides of a product by including mirrors, with almost no disruption of the manufacturing process as the process can be automated and the physical setup does not interfere with the entering and exiting movement of the product on the conveyor belt. Therefore, this design would eliminate the need for multiple cameras and could significantly lower the need for operator time which leads to cost reduction of implementing and running the QI process.
2. Research Design and contributing publications

After the idea of an improved Image Based QI design was set, a literature review was conducted in order to gain more insight about the current research state on this topic, specifically what the research gaps are. This work supports the assumption that there is a lack of research on the topic of QI design in regards to the inclusion of mirrors and Graphical Optics to improve the single camera based design. It is important to know that this research was conducted in 2021 and more papers might have been published after this time and therefore were not included in the review [3]. The design does not include complex ST for operators to use, is noninvasive of manufacturing processes on conveyor belts, and can be constructed as a low cost automated process.

Abilities of this process had to be tested such as the main purpose of identifying defects on all sides of a product, the ML model Accuracy, Sensitivity, Specificity, Precision, and Negative Predictive Value. A research method was derived to address the identified research gap. The fitting quantitative research method is the experimental method. Based on Mishra and Alok’s work, quantitative research is based on the aspect of quantity or extent [20]. The method is used for research that uses systematic experimental analysis of observable phenomena via statistical, mathematical, or computational techniques which result in terms of numerical form [20]. The experimental method was chosen due to the need to test the analytical ability of the proposed design. The design construction was of a single camera setup with a camera box and mirrors (Fig. 3.1). Due to the use of ML, the software was given training data, tested with a new dataset and this data was analyzed for efficiency. Apart from ML being an important asset of the new Industrial Revolution, Benediktsson et al. highlight that the benefits of Neural Network approaches in comparison with Statistical methods are superior [21]. A more detailed explanation of the experiment design segment can be found in the Methodology section of this paper. To gather results after data was collected from the experiment, a Confusion Matrix was used to evaluate the model from which conclusions were drawn. The design structure of this research was an integral part of this work (Figure 3.0.1).
Fig. 3.0.1 Design Structure of the research
3. Methodology

This section explains the setup and methods of the experiment in more detail. To answer the research questions presented in the introductory section, there are two main aspects of the experiment to consider: Physical and Software setup. The Physical setup simulates a manufacturing QI process and consists of a camera box which creates a space which protects from light pollution, mirrors that aid a camera to capture data in form of images, a computer which receives data for processing, and stands for mirrors and the product. The Software setup has a Python environment which contains algorithms for data training and data testing.

4.1 Physical setup

Data was collected from a visual inspection station which was in addition to an eight station Cyber-Physical lab (CP lab) system that functions as a “Learning Factory”. The eight stations consist of workpiece magazines, measuring, heat treat, flipping, pressing, inspection and dispensing applications (A picture of the system is shown in Fig.4.1.1). The full description of the system can be found on Festo’s website [22]. The product passes through the stations in loop multiple times. The visual inspection station was set up besides this system since there is not enough space between the original stations.

![WVU CP Lab System](image-url)
The design setup (Fig.4.1.3) consists of the following core parts: a product to be inspected, product carrier, two sets of two adjustable stands for the mirrors, 4 mirrors, a camera, a light photography box, and a computer. We are photographing smaller products, and so use of a photo box is considered a good solution for light pollution in photos (Fig.4.1.2).

![Fig 4.1.2 – Assembled Photo Box: (A) Showing top camera placement and (B) inside environment](image1)

![Fig 4.1.3 - CAD design of the QI station inside the camera box](image2)
Fig. 4.1.4 - CAD design of the QI station without camera box outline and camera

The placement of the mirrors shown in Figure 4.1.3 and Figure 4.1.4 was designed based on the Geometrical Optics law of reflection. The mirrors had to reflect their respective side of the product towards the camera while not interfering with the product entrance and exit from the station. Figure 4.1.5 shows picture distortion due to mirror placement. The red line showcases the space needed for the object to enter the processing area. The light blue lines represent light projections of the workpiece onto the mirror and then to the camera. It can be seen that the length of the image reflected upon the mirrors, d1 and d2, are different. At a smaller angle, the length is larger. Since a larger photo would showcase a defect as larger and therefore better presented to the ML system, the angle chosen for this experiment is 40°. Though the angle was set for the experiment, the mirror stands are designed to be adjustable as shown in Figure 4.1.6. This means that the mirror angle and distance between the mirror and product/camera can be changed based on preference. The camera that was used had a wireless Bluetooth option (Fig.4.1.7). It was attached to the photo box at the top which allowed it to take a top view picture. It sent the photo to a nearby computer for further processing.
4.2 Workpiece

The product that was inspected is a workpiece (Fig.4.2.1 (A)). This is originally a Festo CP Lab product. The workpiece consists of two parts: the top and bottom housing. The assembled workpiece was
inspected. To simulate a manufacturing process performed in a sequence on a conveyor belt, the workpiece was placed on a Festo original carrier shown in Fig.4.2.1 (B). The carrier was then placed on the conveyor belt which is represented by a block (Fig.4.1.3 and Fig.4.1.4).

Fig.4.2.1- (A) Festo’s Cyber Physical Lab mobile case and (B) CAD design of the workpiece and carrier

Due to the housing being already produced by Festo and inspected before being sent to our lab, there are no visible defects. Because of this, during the training and testing datasets processes, parts needed to have added defects. Some manufacturing defects are excess material (Fig.4.2.2) or scratches (Fig.4.2.3). Excess material can be a result from three-dimensional printing [23] or molding processes [24] etc. Scratches can result from the grinding process [25] or molding process [23] [26] etc. Therefore, these types of defects were randomly added on the five sides of 31 workpieces (Table 4.2.1).

Fig.4.2.2- Defect type in production: Excess material [23]

Fig.4.2.3- Defect type in production: Scratches [26]
<table>
<thead>
<tr>
<th>Side</th>
<th>Top</th>
<th>Left</th>
<th>Right</th>
<th>Up</th>
<th>Down</th>
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<tr>
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<tr>
<td>Scratch</td>
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<td><img src="image14.png" alt="Image" /></td>
<td><img src="image15.png" alt="Image" /></td>
</tr>
</tbody>
</table>

Table 4.2.1 – Visual representation of examples of defect types on each of the five sides
The mirror frames and adjustable stands were 3-D printed and fixed to a blackboard along with Festo assembly line rails and carrier, shown in Figures 4.2.4 and 4.2.5.

Fig.4.2.4 – Side view of the final Multisided Image Based QI Station

Figure 4.2.5 – Sample of all side non-defective datapoint
4.3 ML Models and Data Collection

There are multiple types of ML models, such as more commonly used supervised and unsupervised [10]. Unsupervised models attempt to find natural partitions of patterns [27]. They require a larger set of datapoints than available for this experiment due to resource restrictions. Supervised learning is preferable for this case because it uses labeled training datasets to prepare models to classify data or predict outcomes accurately. The model is continuously measured for accuracy until error is minimized sufficiently, this is done through loss function [27]. They are very common and provide high accuracy for manufacturing and Image Based QI [28][29]. Furthermore, classification is a type of supervised learning which uses an algorithm to classify the data from the testing dataset into the right categories. For this experiment, the ML model was used to recognize between defect types and a non-defect, and attempt to classify them into their respective category.

The photos were collected by the computer and processed by the Python software. There are two sets of algorithms that helped collect and sort, clean and analyze the training data set and then the test data set. To choose a fitting sample of training data, research on Neural Networks was conducted and indicates that there are risks of too little data which leads to low test accuracy [30] and overtraining and overfitting which cause a lower predictive power [31]. There are two common errors that arise from this; overfitting and underfitting. Underfitting is the model’s inability to represent datapoints usually due to a small dataset. Overfitting is when the model represents the datapoints too accurately which leads to inability to perform well with unseen data [32]. The two datasets are different because if the two datasets were equal the model would be overfitting and the model showcased an inability to perform well with new data. It is also important to mention that good accuracy with training data does not guarantee it with new/unseen data (testing data) [32]. Due to resource restrictions, the available number of training data is 47 datapoints. Both training and testing datasets included non-defective and defective workpieces with randomly placed defects, see section 4.2. This is so that the models are trained to predict non-defective and defective products. The testing dataset consisted of 13 datapoints. This decision is based on the
common split ratio of 70:30, training and testing data respectfully. It is important to indicate that the testing and training datasets are separate. The reason for this is that ML requires a training dataset so it can learn the patterns that best represent the dataset. Training dataset helps the model learn while the testing dataset evaluates the ability of the model.

4.4 Data Preprocessing

The collected photos (Fig.4.2.4) were of high quality which, if not preprocessed, would cause a large model training time. To cut this time, a preprocessing algorithm was written to exclude parts of the photograph that were constant and only include the workpiece. Figure 4.4.1 shows the algorithm used to obtain photos of individual five sides of the workpiece. First line of code is calling for the library that was used called “Pillow” (PIL). This library is used for opening, manipulating, and saving image of different file formats. Next line is opening the image we wish to process, in this case file name “001.JPG”. The rest of the lines of code first address the location of the desired area in the image and then crop it to create the top, left, right, up, and down sides respectfully. After all the preprocessing and grouping of defective and non-defective datapoints, the first two lines shown in Figure 4.4.2 call the datapoints “xi” and their respected labels “yi”, where i=1…5 for corresponding sides (down, left, right, top, and up). The values of the features range from 0 to 255 and so they were scaled down to 0 to 1 range in the last line. The last part of preparing the data for the ML process was to separate the randomized dataset into training and testing datasets based on the 70:30 rule mentioned previously (Fig.4.4.3)
```python
from PIL import Image
im = Image.open('001.jpg')

test_top_left = 950*890
test_top_top = 1225-45

test_top_right = 1010*1190

test_top_bottom = 1760*85

top_test = im.crop(((test_top_left, test_top_top, test_top_right, test_top_bottom)))

test_left_left = 950

test_left_top = 1225

test_left_right = 1010


test_left_bottom = 1760

left_test = im.crop(((test_left_left, test_left_top, test_left_right, test_left_bottom)))

test_right_left = 950*2100-65


test_right_top = 1225-30

test_right_right = 1010*2100


test_right_bottom = 1760-20

right_test = im.crop(((test_right_left, test_right_top, test_right_right, test_right_bottom)))

test_up_left = 950*945

test_up_top = 1225-870

test_up_right = 1010*1190


test_up_bottom = 1760-1320

up_test = im.crop(((test_up_left, test_up_top, test_up_right, test_up_bottom)))

down=2210

test_down_left = 950*945

test_down_top = 1225-870+2210

test_down_right = 1010*1190

test_down_bottom = 1760-1320+2210

down_test = im.crop(((test_down_left, test_down_top, test_down_right, test_down_bottom)))

x4=pickle.load(open('x4.pkl','rb'))
y4=pickle.load(open('y4.pkl','rb'))
x4=x4/255 #feature scaling (0-255 now 0-1)

x4_train=x4[0:34]
y4_train=y4[0:34]
x4_test=x4[34:47]
y4_test=y4[34:47]
```

Fig. 4.4.1 – Python algorithm used to preprocess the photos

Fig. 4.4.2 – Python algorithm for calling the datasets and reshaping

Fig. 4.4.3 – Algorithm separating Test and Training datapoints
4.5 Supervised ML software

After research into most suitable Python libraries and existing algorithms for supervised ML, the Keras library proved to be the optimal fit in regards to simplicity, training speed, and data storage (Fig.4.5.1). The algorithm used for this research was not newly developed but adapted from the existing repository. Keras is a free Python library used for ML and includes TensorFlow which is a programming infrastructure layer used for N-dimensional arrays (tensors) [33]. These were needed in order to code classification ML models (Fig.4.5.2 and Fig.4.5.3). Classification is a type of Supervised ML where datapoint features (such as workpiece images) and labels (such as “defective” and “non-defective”) are used to train the model and the model is then used to predict the labels of the test dataset [34]. A Convolutional Neural Network (CNN) model has high performance in ML problems such as image recognition [35][36]. The input (image) and output (label) of the model are predetermined and the predicted output is compared with the actual output. The model learns by adjusting its parameters based on the error and adds it to the CNN. The model first obtains abstract features and works towards deeper layers [10][35]. CNN’s have been very popular due to the amount of developed variations which can address a variety of problems. They have been largely used in image recognition problems [36] which is why a CNN was chosen for this design.

```python
from keras.models import Sequential
from keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
from tensorflow.keras.callbacks import TensorBoard
from tensorflow.keras.models import Sequential

model4 = Sequential()
model4.add(Conv2D(64, (3, 3), activation='relu'))
model4.add(MaxPooling2D((2, 2)))
model4.add(Conv2D(64, (3, 3), activation='relu'))
model4.add(MaxPooling2D((2, 2)))
model4.add(Flatten())
model4.add(Dense(128, input_shape=x4.shape[1:], activation='relu'))
model4.add(Dense(1, activation='sigmoid'))  #1 softmax
model4.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
```

Fig.4.5.1 – Python Libraries employed

Fig.4.5.2 – Algorithm employing CNN
4.6 Design acceptance level

Since this work is being done under the assumption that the ML process can more accurately detect and classify defects on the top of the workpiece, this ability of the system was compared with the ability to accurately detect and classify the defects on the other four sides individually. A Confusion Matrix (Table 4.6.1) serves as an evaluation of a supervised classification model [37]. The overall accuracy obtained using the Confusion Matrix is shown in Table 4.6.1. Description of the variables is as follows:

1. True Positive (TP): Observation is positive and classified as positive by the model.
2. False Negative (FN): Observation is positive but classified as negative by the model.
3. True Negative (TN): Observation is negative and classified as negative by the model.
4. False Positive (FP): Observation is negative but classified as by the model.

<table>
<thead>
<tr>
<th>Actual observation</th>
<th>Observation classified by the model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>Positive</td>
</tr>
<tr>
<td></td>
<td>TP</td>
</tr>
<tr>
<td></td>
<td>FN</td>
</tr>
<tr>
<td></td>
<td>(Type II Error)</td>
</tr>
<tr>
<td>Negative</td>
<td>FP</td>
</tr>
<tr>
<td></td>
<td>(Type I Error)</td>
</tr>
<tr>
<td></td>
<td>TN</td>
</tr>
</tbody>
</table>

Table 4.6.1 – Confusion Matrix [37]

Sensitivity is the proportion of the total number of TP out of the sum of Condition Positives (TP and FN). It is determined by the Equation 4.6.1:

\[
Sensitivity = \frac{TP}{(TP+FN)}
\]

Eq.4.6.1 – Formula for finding the Sensitivity of the model using the Confusion Matrix [37]
Specificity is the proportion of the total number of TN out of the sum of Condition Negatives (TN and FP). It is determined by the Equation 4.6.2:

\[ Specificity = \frac{TN}{(TN + FP)} \]

Eq.4.6.2 – Formula for finding the Specificity of the model using the Confusion Matrix [37]

Precision is the proportion of the total number of TP out of the sum of Outcome Positives (TP and FP). It is determined by the Equation 4.6.3:

\[ Precision = \frac{TP}{(TP + FP)} \]

Eq.4.6.3 - Formula for finding the Precision Predictive Value of the model using the Confusion Matrix [37]

Negative Predictive Value is the proportion of the total number of TN out of the sum of Outcome Negatives (TN and FN). It is determined by the Equation 4.6.4:

\[ Negative \ Predictive \ Value = \frac{TN}{(TN + FN)} \]

Eq.4.6.4 - Formula for finding the Negative Predictive Value of the model using the Confusion Matrix [37]

Based on the model accuracy (Eq.4.6.5) of the experimentation, a conclusion was drawn whether addition of mirrors to create multisided system design identify defects on four sides of the part in the distorted mirror images.

\[ Accuracy = \frac{TP + TN}{(TP + TN + FP + FN)} \]

Eq.4.6.5 – Formula for finding the Accuracy of the model using the Confusion Matrix [37]
4. Results and Discussion

This section provides and discusses results of this research. Here you will see the results of data preprocessing, ML model output, and Confusion Matrix evaluations for models made for each side of the workpiece. Finally, this section discusses the design’s ability to evaluate all five sides of the workpiece similarly.

5.1 Data Preprocessing

In sub-section 4.4 it was mentioned how data needed to be preprocessed in order to avoid evaluating the background, more accurately evaluate each individual side and speed up the model training and workpiece evaluation processes. Figure 5.1.1 below shows the output of a single original datapoint (Fig.4.2.4) preprocessing. These separate new datapoints represent a much smaller area of the original and so require less data storage and processing power.

![Fig.5.1.1 – Resulting 5 non-defective datapoints from initial photo (Fig.4.2.4)](image-url)
5.2 Top Side Model Output and Confusion Matrix

This subsection shows the data outputs of the top side of the workpiece which was not reflected by mirrors and had no image distortion. These results were used as a baseline for the ML model and they were, in the end, compared with results given by the models of the rest of the workpiece sides in order to conclude whether or not mirrors can be used in the design of automated QI stations.

The following results represent the original image and a thermal image of where the software recognizes the defect (green color) (Fig.5.2.1 and Fig.5.2.2). Some images might have defects hard to recognize with a naked eye, but the software was overall able to recognize if there were defects with a 92% accuracy. Completing the Confusion Matrix, it can be seen that only one prediction was incorrectly labeled as not defective while 4 defects were correctly found along with 8 non-defective correctly labeled (Table 5.2.1).

![Fig.5.2.1](image1.png)

(A) Original datapoint (B) Thermal image

![Fig.5.2.2](image2.png)

(A) Original datapoint (B) Thermal image
Fig. 5.2.3 – Human inspection results of top side test set

Fig. 5.2.4 – Model inspection results of top side test set

Table 5.2.1 – Results from model assessment using the Confusion Matrix for the top side model

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>Positive</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>1</td>
</tr>
<tr>
<td>Negative</td>
<td></td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>8</td>
</tr>
</tbody>
</table>

Table 5.2.1 – Results from model assessment using the Confusion Matrix for the top side model

5.3 Mirror reflected Side Models Output and Confusion Matrix

This subsection shows the data outputs of the sides of the workpiece which were reflected by mirrors and image distortion (Fig. 5.3.1 to Fig. 5.3.8). The following results represent the original image and a thermal image of where the software recognizes the defect (green color) (Fig. 5.3.1 to Fig. 5.3.8). In these cases the software was overall able to recognize if there were defects with a 90% overall accuracy (Fig. 5.3.9 to Fig. 5.3.16). Completing the Confusion Matrix, it can be seen that five predictions in total were incorrectly labeled as defective one by the down side model, two each by the up and right side models, and none by the left side model. It is interesting to note that there were no missed defects by any of the models. A total of 11 correct defective and 36 non-defective predictions (Table 5.3.1 to Table 5.3.4).
Fig.5.3.1 – Right side with excess material: (A) Original datapoint (B) Thermal image

Fig.5.3.2 – Right side with a scratch: (A) Original datapoint (B) Thermal image

Fig.5.3.3 – Left side with excess material: (A) Original datapoint (B) Thermal image
Fig. 5.3.4 – Left side with a scratch: (A) Original datapoint (B) Thermal image

Fig. 5.3.5 – Up side with excess material: (A) Original datapoint (B) Thermal image

Fig. 5.3.6 – Up side with a scratch: (A) Original datapoint (B) Thermal image
Fig. 5.3.17 – Down side with excess material: (A) Original datapoint (B) Thermal image

Fig. 5.3.8 – Down side with a scratch: (A) Original datapoint (B) Thermal image

Fig. 5.3.9 – Human inspection results of right side test set

Fig. 5.3.10 – Model inspection results of right side test set
Fig. 5.3.11 – Human inspection results of left side test set

Fig. 5.3.12 – Model inspection results of left side test set

Fig. 5.3.13 – Human inspection results of up side test set

Fig. 5.3.14 – Model inspection results of up side test set

Fig. 5.3.15 – Human inspection results of down side test set

Fig. 5.3.16 – Model inspection results of down side test set

<table>
<thead>
<tr>
<th>Actual</th>
<th>Predicted</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Positive</td>
<td>Positive</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>0</td>
</tr>
<tr>
<td>Negative</td>
<td>Positive</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Negative</td>
<td>8</td>
</tr>
</tbody>
</table>

Table 5.3.1 – Results from model assessment using the Confusion Matrix for the right side model
5.4 Summary of Results

This subsection discusses obtained results, provides answers to the research questions from subsection 1.2, and gives recommendations. The literature review section discussed how inclusion of mirrors in the Image Based QI design has not been researched which answers the first research question.

Based on the evaluated predictions of each ML model (Table 5.4.1), all the models have an 85% or above accuracy. This wider accuracy range was expected as there was not a large dataset available to test the model and each prediction carried about ±7.7% accuracy change (one out of thirteen). It is interesting to see that the mirror reflected sides found all of the defects while the non-reflected side found 80%. In this case, the designed process was able to successfully identify all of the defects from the mirror distorted images.
Table 5.4.1 – Model evaluation results

The difference between the results of the non-reflected (top) side and the reflected sides is minor based on evaluation of their accuracy. After performing evaluations presented in Table 5.4.2 and 5.4.3 below, it can be seen that the non-reflected side had better Specificity and Precision while Sensitivity and Precision were better on average of mirror reflected sides. Specificity results indicate that the non-reflected image prediction model’s percent certainty of workpieces labeled as non-defective is higher by 12% in comparison to the average reflected models’. Precision results indicate that the non-reflected model is 31% more likely to correctly alarm that the defect was found. Sensitivity results indicate that the non-reflected model is 20% less likely to detect a defect than the defective model. Negative Predictive Value results indicate that the non-reflected model is 11% more likely to incorrectly alarm that the defect was found. These results indicate that both reflected and non-reflected image models have their strengths and weaknesses in comparison to each other but both have the ability to correctly identify defects and non-defects.

<table>
<thead>
<tr>
<th>Side</th>
<th>Accuracy</th>
<th>Found defects [%]</th>
<th>False alarms [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Down</td>
<td>92%</td>
<td>100%</td>
<td>25%</td>
</tr>
<tr>
<td>Up</td>
<td>85%</td>
<td>100%</td>
<td>40%</td>
</tr>
<tr>
<td>Left</td>
<td>100%</td>
<td>100%</td>
<td>0%</td>
</tr>
<tr>
<td>Right</td>
<td>85%</td>
<td>100%</td>
<td>40%</td>
</tr>
<tr>
<td>Top</td>
<td>92%</td>
<td>80%</td>
<td>0%</td>
</tr>
</tbody>
</table>

Table 5.4.2 - Top ML model evaluation results

Table 5.4.3 - Average of mirror reflected side ML models evaluation results

The recommendations based on research and the results of this paper are to include QI processes in manufacturing in order to gain insight on defect patterns in order to identify causes earlier. There is an
increase in research on this topic which can lead to simpler, lower cost, less time consuming and overall better fitting Image Based QI for a variety of products. This paper’s proposed process design is simpler, solves the multiside inspection problem at a lower cost than including multiple cameras or 3D scanning equipment, and lowers operator and overall processing time due to its simplicity and automation ability. The size, distance and adjustability of the design enables parameter corrections based on the product type.
6. Conclusion and Future Work

This study proposed a new Image Based QI design setup and tested its ability to find and alert defects on products. The literature review showcases a growing interest in QI since the public introduction of the Fourth Industrial Revolution in 2011. [3] which supports the need for further research and improvement in this area of manufacturing. There was no research on Multisided QI using mirrors found at the time the literature review was conducted. The results of this work showcase that the proposed system can identify defects on four sides of the part in the distorted mirror images at a similar accuracy rate as the top part which was directly showcased (not using the mirrors).

While the results overall are valuable and interesting, some limitations of the work need to be discussed. The author’s understanding of the problem was under certain assumptions, time, and resource limitations and there is possible bias in the interpretation of the results. These issues were addressed by creating a transparent methodology and applying the four-eye principle where the work was reviewed and approved by the thesis committee.

Due to resource and time restraints, this experiment was done on a separate station from the assembly line with a small dataset. It would be beneficial to conduct an experiment with the proposed QI process connected onto the assembly line, gather a larger dataset and/or inspect different types of products. This expands the experimentation ability towards an Unsupervised ML model whose accuracy depends on a larger dataset as previously discussed in section 4.2. Additionally, a comparison between other image or Operator Based QI and this design would provide insight on the benefits/disadvantages of this work’s proposed design.
5. Acknowledgments

I am grateful and proud of my time at West Virginia University. This project would not have been possible without the support of many people. First, I would like to express my immense respect and gratitude to my research supervisor Dr. Thorsten Wuest for his guidance and support during the span of this research.

I am also grateful to the committee members Dr. Imtiaz Ahmed and Dr. Bin Liu for their valuable insights and feedback over the course of this thesis which helped significantly improve the quality of this research.

I wish to thank my family, colleagues and friends, who endured this long process with me and with whose prayers and constant support I was able to complete this important life milestone.
8. References


dFrom%3dgeometrical%2boptics#eid154883973