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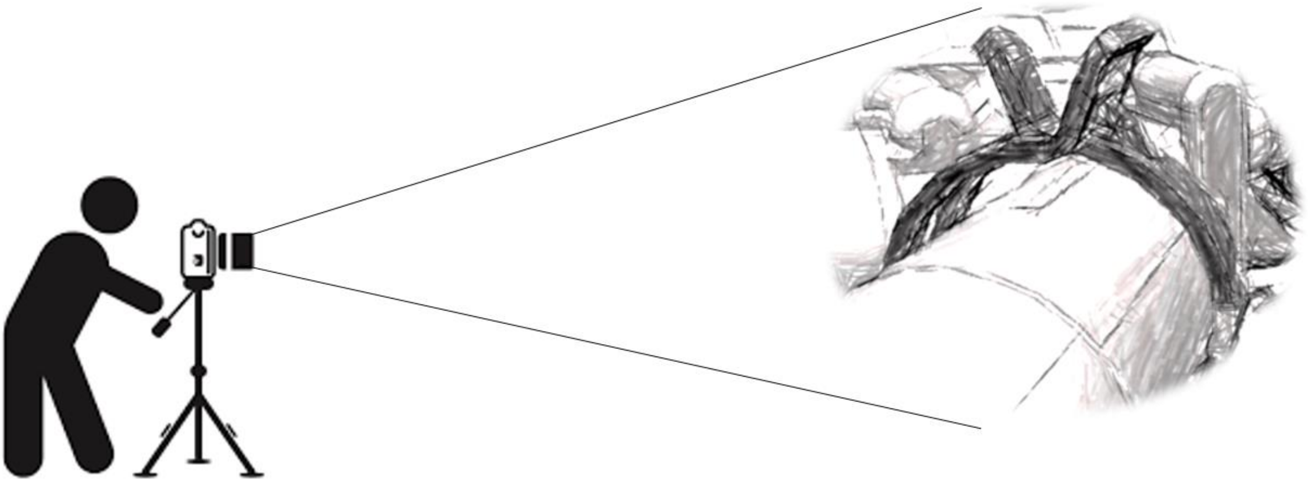

# Implementing AI vision for Quality Inspection within a Manufacturing Environment

## A study to Explore the Functionality of Detecting Deviations in Manual Assembly

Master's thesis in Production Engineering

MATILDA WOLLTER BERGMAN

DEPARTMENT OF INDUSTRIAL AND MATERIALS SCIENCE

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Cover: Illustration of detecting a clamp made by Matilda Wollter Bergman

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## Abstract

All manufacturing companies strive to ensure high quality for their products, not least concerning manual assembly, in order to remain competitive. Despite all preventive strategies available to eliminate the occurrence of deviations, additional reactive quality inspections are sometimes required. These are primarily performed by humans since they are flexible and can easily be placed wherever needed and learn new tasks. However, there are also drawbacks with using manual inspections, as these tasks are both demanding as well as costly to implement. Therefore, companies now seek to take advantage of the constant technological development to explore new methods that are both cost-efficient and easy to install quickly, wherever needed. This thesis presents an explorative study about implementing a suggested cost-efficient AI vision system to detect product deviations in manual assembly. The study emphasises both drawbacks and advantages of the technology in its current state. Through exploratory testing, several impactful factors were identified that influence the results of AI vision. A robustness test was thereafter conducted to evaluate the system's sensitivity towards changes. This was done to establish requirements and limits for implementation. Lastly, a suggested setup for implementation was tested in a manufacturing environment to validate the findings from earlier testing.

Keywords: *AI vision, Quality, Quality inspection, Product deviations and Manual assembly*

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Matilda Walter Bergman

Gothenburg Sweden, December 2021

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# Glossary

| | |
|---|---|
| AI | Artificial intelligence |
| ML | Machine Learning |
| Contrast | Contrast regulates the degree of difference between two colours or between the lightest lights and darkest darks in an image thus making objects more distinguishable. |
| Brightness | Brightness regulates how dark or light a picture is. Correct brightness is important to easily understand the contents of the picture. Changing the brightness of a picture affects all pixels equally. |
| Saturation | Saturation is the purity of a colour and can make an image appear more vivid and intense. Saturation levels will affect the way that colours appear in different lights. |
| Zoom | Zoom means to make the object larger (or smaller) in the image without actually moving the camera. With optical zoom, the glass elements inside the lens move to increase or decrease the focal length of the lens which retains as much image quality as possible. Digital zoom does not however use the lens's optics, only allocates more pixels to the 'zoomed' portion of the optical image, which results in lower resolution than optical zooming. |
| Focus | Focus means adjusting the camera lens so that the object achieves maximum sharpness in the image. If there is no proper focus, the image will end up blurry, that is unsharp, images even when all the other camera settings are correct. Focusing can be easy or difficult depending on what to detect, like a non-moving landscape versus a fast-moving bird in flight. |
| Sharpness | Sharpness describes the clarity of detail in a photo, and is ultimately limited by the camera equipment, image magnification and viewing distance |
| White balance | White balance is used to adjust colours to match the colour of the light source so that white objects appear white |
| Monochrome | Monochrome settings means that the images are displayed in black and white nuances and no colour |
| Prediction | The AI vision's selection of classifying the object's state after ML |
| Precision | The correctly classified states divided with total number of predicted images in the same state |
| Recall | The correctly classified state divided with the total number of input images in the same state. |

# 1 Introduction

Quality inspection during assembly is important for all manufacturing companies, it is therefore also important to continuously improve.

## 1.1 Background

Manual assembly is often applied in manufacturing industry. Despite implementation of different error proofing strategies, errors occasionally happen as manual assembly work is highly demanding to perform [1]. Mistakes that occur during the production process result in consequences for the company, such as increased financial costs and damaged brand reputation [2]. It has been found that it is necessary to supplement pre-emptive actions, such as strategies for designing assembly solutions, with reactive inspections [3]. These additional quality inspections must be reliable and ensure detection of all deviations. Each action that could contribute to upholding delivery of high-quality products is crucial to remaining competitive within the market [4].

Manufacturing companies seek to maintain competitiveness by developing standard procedures to assure the quality of their manual assemblies [5]. These are foremost integrated within the production process. It could for example be various inspection plans or random testing through visual inspection and measurements [6]. The integrated quality management systems are designed to detect deviations during production as well as ease detection at early stages.

There are many different methods and technologies available on the market to assist detecting deviations already, both preventive and reactive [5]. Although these technical solutions become gradually more cost-efficient to implement, they are still time consuming and require permanent installations connected to the production system. Hence, it is beneficial to develop aids that assist the detection of deviations in the production process. These aids should be cost-efficient and easy to install fast wherever needed.

## 1.2 Problem description

The manufacturing industry now seeks to further explore newer solutions for performing quality inspection that take advantage of today's advanced technology. A proposal has been made by a case company to evaluate the possibility of using a specific combination of hardware and software to visually detect deviations during manual assembly. The combination is the camera, *Logitech c922 pro hd stream webcam* and the machine learning software, *AutoML*. This combination is designated by the company to be cost-efficient and easy to install quickly wherever needed. The challenge is to reach a reliable result in a manufacturing environment with all the requirements that come with it.

## 1.3 Aim and purpose

This empirical study aims to explore the possibility of implementing AI vision in a manufacturing environment to accurately detect assembly deviations using a specific combination of hardware and software, which is presented in section 1.2. The study will further serve to help companies determine whether or not to invest in this technology at its current level of development.

## 1.4 Research questions

The following three research questions are addressed:

RQ1: *What makes a manual assembly suitable to be detected by the AI vision in a manufacturing environment?*

RQ2: *What setup conditions limit the usage of AI vision for quality inspection*?

RQ3: *What affects the machine learning process of the AI vision when stiving to achieve a low error rate?*

## 1.5 Limitations

The thesis is limited by only investigating one manual assembly operation in a manufacturing work environment at the final stage of the manufacturing process. A free trial of the software *AutoML* is used for this study which limits the number of tests performed. All data transportation will be performed through a cable and not wireless because focusing on data transportation might detract from exploring the AI vision’s functionality. Lastly, the thesis will not include integrating the AI vision and software with any internal production systems at the company.

# 2 Theoretical frameworks

The following chapter will present relevant theory to provide background of current practice. The three main subjects that will be presented are: background information about quality management, current applicability of AI vision, and applicability of Machine learning.

## 2.1 Quality Management

There are many ways for a manufacturing company to measure quality. However, two of the primary dimensions to consider are product quality and customer satisfaction [7]. Product quality can be measured objectively by the number of defects, while customer satisfaction is based on the subjective judgement regarding both service and overall product impression. For example, it has been found that customer satisfaction increases loyalty to a particular brand or company [8]. Nonetheless, to solely rely on customer satisfaction for measuring and improving quality is not recommended [9]. A combination of customer satisfaction and product quality is further proposed, as a clear interaction between these has been identified as a reliable measurement of quality [2]. The importance of providing customers with products of high quality has been established as vital for manufacturing companies to remain competitive [4]. The term quality, however, in this thesis refers to product quality.

Lean manufacturing approaches seek to directly ensure quality of a product immediately after leaving a workstation to minimise unnecessary rework [10]. This approach is called *First Time Through* (FTT). FTT is a common applied philosophy at manufacturing companies because assembly errors have been emphasised as very costly for the company to detect and correct [11] [12]. For example, detecting product deviations late in the process tends to create bottlenecks in the production flow [6]. This could be caused by either starvation or blockage which means that the production line sits idle because a workstation cannot feed forward or does not receive any products from earlier workstations. Centralisation of quality inspection in production is therefore not sufficient [13]. Other important aspects of quality errors are increased scrap rate which impacts the environment negatively and increases waste of resources required for rework and disassembly [14].

### 2.1.1 Reasons for quality deviation in manual assembly

It has been acknowledged that fully eliminating errors that occur during manual assembly is impossible because occasionally making mistakes is a consequence of being human [15]. Earlier studies emphasise that physical and/or cognitive ergonomics has a clear influence on product quality [16] [17]. Poor assembly ergonomics could result in decreased product quality as demanding work tasks limit the operators' possibility to assemble correctly. For example, it is highlighted that having cognitive demanding work conditions, such as time pressure and stress, lowers the ability to focus on quality during assembly [1]. In addition, having overbalanced workstations contributes to improper assembly [17]. Furthermore, the recent requirement of high levels of customised production also contributes to an enlarged risk of deviations. The resulting increased product variability enhances challenges in assembly [18]. For example, the effort required when constantly having to make choices and select the correct item is demanding for the operator [11]. Moreover, it has been established that the degree of work task complexity affects the manual assembly negatively.

### 2.1.2 Strategies to improve quality in manual assembly

Upholding the quality level requires reliable methods to detect any occurrence of deviations, both preventive and reactive. Applying preventive actions in production has for example been found to contribute to delivering high quality products and lowering production cost per unit [19]. One example of preventive actions is the strong mindset among design and manufacturing engineers to create simple assembly solutions that cannot be performed incorrectly [1]. The mindset is used to eliminate the risk of errors and thus increase product quality. Moreover, a common strategy within manufacturing industry is Failure Mode Effects Analysis (FMEA). FMEA is a preventive work tool, often applied to identify all potential failures within a production process before implementation [3]. By removing the identified potential failures beforehand, this optimised solution will contribute to enhanced quality. The preventive work tool Methods-Time Measurement (MTM) has also been proven to be helpful during design of manual assembly workstations to decrease overload [20]. Evenly distributed work tasks at each workstation contribute to a lower error rate. Another important approach to avoid deviations in manual assembly is well written work instructions [21]. For example, the instructions must be presented in such a way that anyone can understand them and conduct assembly accordingly. Furthermore, it has been proposed that quality in production is improved by introducing kitting [22]. Kitting implies that operators receive a set of items to be assembled in a certain sequence at each workstation [23]. This approach helps to eliminate the risk of incorrect assembly by removing the step of selecting the right item as well as being guided through the mounting sequence [24]. Providing proper training to personnel also contributes to decreasing the risk of incorrect assembly [1].

After assembly, additional visual inspection is a vital reactive action to detect deviations [25]. This visual inspection has been performed by humans for many years through self-control or by another assembler. Manual inspections are often applied as humans are flexible and easily adapt to new tasks. Sufficient time for conduction and appropriate work condition has been established as facilitating the inspection [26] [27]. For example, the performance of self-control will be improved by the operator's inner motivation such as professional pride i.e., self-realisation [28] [1]. However, manual inspection has been identified as a very monotonous work task that places high demands on the single individual [16]. In addition, the method is not considered cost-efficient since it is expensive to introduce at short notice as well as to maintain. It has also been stated that using automatic quality controls to detect deviations has advantages to manual [14]. Therefore, automatic visual inspection in manufacturing has been introduced in recent years. One example is image acquisition to inspect, sort and detect deviations e.g., incorrect assembly or missing items [29]. Moreover, there are different systems used for tracking errors after detection such as *Atacq* (at line production reports), *TRACY* (local plant blocking system) and Product Verification System (PVS) [16].

## 2.2 AI vision

AI vision refers to using computers in combination with visualisation to simulate human behaviour such as judgment and decision-making [30]. A digital camera based on pixels is used to visualise and interpret situations. However, investing in AI vision cameras is expensive which limits its use. Additional consideration before implementation is therefore required.

Detecting shapes and deviations by using AI vision has already been proven to be successful [31]. Studies have shown that object recognition can be used to easily distinguish and memorise several product variants and thereafter sort them correctly [29]. The AI vision can thereby enhance the level of standardisation of the products as well as monitor various activities to optimise processes [32]. Another successful example is detecting defective surfaces on manufacturing products [33]. Despite these successful implementations of the AI vision, detecting deviations related to complex objects and complicated structures could hinder performance [14]. Consequently, it has been proposed that binary defects are more appropriate, e.g., opened or closed. It has also been highlighted that background disturbances as well as small size of object affect the performance negatively.

One drawback of applying AI vision is the system's inflexibility because its ability to interpret data is limited [32]. The system cannot handle unpredictable situations well. For example, the AI vision's performance could be reduced by uncontrollable disturbances. It is therefore important to carefully consider the suitability of work tasks when proposing implementation.

## 2.3 Machine learning

Machine learning (ML) is a way to make AI vision feasible [30]. The approach that ML is based upon uses algorithms which could be improved by learning from data [34]. ML enables the computer to learn and analyse a set of data and thereafter automatically make decisions within a real-world situation without the need for human input [35]. The following two ML styles are often applied: Supervised learning and Unsupervised learning, see Figure 1. Moreover, the choice of style is determined by the ML task and type of data for input and output [36].

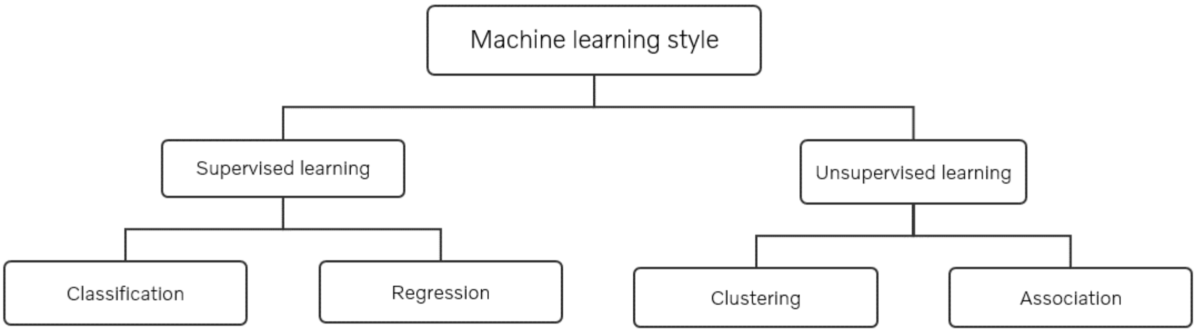


**Figure 1.** *A taxonomy of ML styles*

During supervised learning the system is taught by training a data set with labelled data [37]. The data could be either continuous or categorical. Continuous data is expressed in numbers and analysed through regression [38]. A common use for this type of data is prediction of housing prices. Categorical data refers to a set of data with similar characteristics that is classified e.g., into different labels {True, False} [39]. Moreover, the classification algorithm could be used to teach a visual inspection system [40]. A process overview of AI vision using classification is shown in Figure 2.

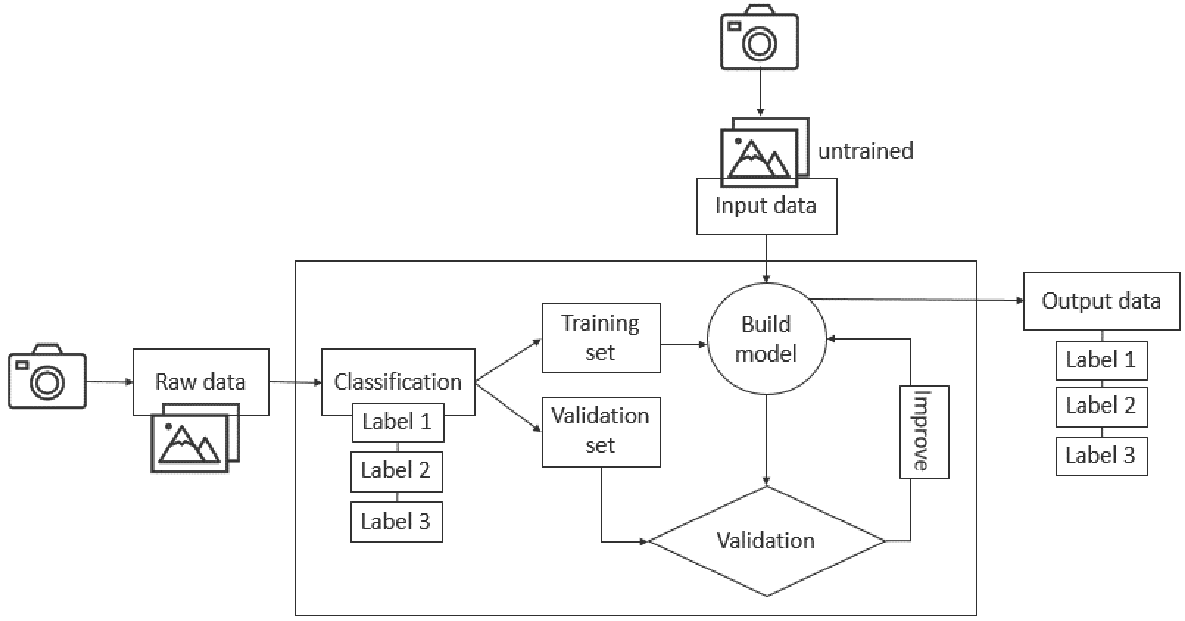


**Figure 2**. *A process overview of supervised learning through classification*

As illustrated in Figure 2, a set of raw data is gathered and inserted to the ML system followed by a supervised classification. The system is thereafter through the algorithm taught to accurately sort data into the different labels. A validation is also performed to optimise the system as much as possible before receiving untrained input data. The last part in the process is an independent sorting of the newly received data according to the pre-trained labels.

In contrast to supervised learning, unsupervised learning uses unlabelled data during ML without a target variable [36]. Judgement is based solely on input data [41]. The algorithms are used to identify patterns through association or similarities by clustering [42]. This type of process could also be referred as Data Mining and is often applied when there is no obvious output to determine beforehand.

# 3 Methodology

To investigate the functionality of AI vision as quality detector in a manufacturing environment, an experimental study approach was taken. The study was therefore designed in accordance with empirical research methodology. Four stages were conducted during the study: Observations of current state, Exploratory testing to identify the impactful factors for the AI vision, Robustness test to screen out the significant factors and lastly a final test to validate or disprove the conclusions made from earlier testing, see Figure 3. These stages are presented in the following subsections.

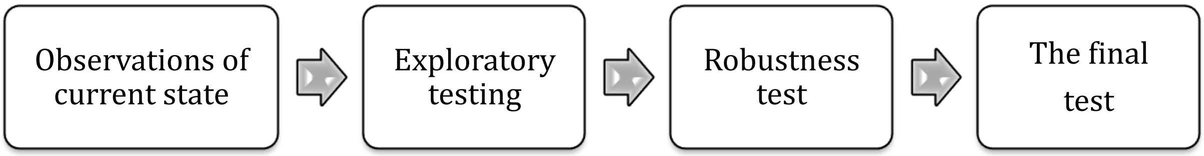


**Figure 3.** *The stages conducted during the study*

## 3.1 Observations of current state

Observations were performed to create a greater understanding of the company’s quality management with regard to manual assembly at final stage. The observation was also performed to gain a more detailed understanding of demands on the solution. The information was collected through observing the manual assembly lines at the company as well as performing unstructured interviews with some manufacturing engineers at the company. Examples of questions asked during these interviews were: 1. *What methods are used to detect deviations within manual assembly?* and 2. *What actions are made to avoid incorrect manual assembly?*

## 3.2 Exploratory testing

The main intention of the exploratory testing was to identify the factors with the greatest impact on achieving low error rates for the AI Vision system and suggest an adequate setup. In order to determine the impactful factors, four main areas were carefully selected: Software settings for machine learning, Camera setup, Environmental factors, and Object to detect. These are presented in later sections. The procedure used for the exploratory testing was based on the five-phase empirical research methodology cycle which was developed by the Dutch psychologist Adrianus Dingeman de Groot in 1940 [43]. It consists of the following five phases: Observation, Induction, Deduction, Testing and Evaluation, see Figure 4.

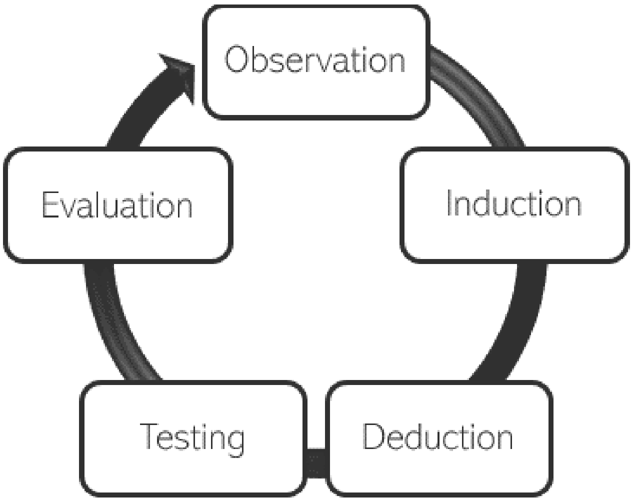


**Figure 4.** *The five-phase empirical research methodology cycle*

The Observation phase was performed to gather valuable information to answer the question addressed [43]. Observations were performed through visual perceptions. The second phase, Induction, refers to inductive reasoning and formulating conclusions without being limited by preconceptions. Moreover, the Deduction phase aimed to combine valuable experience and established knowledge to prepare a hypothesis for Testing. The Testing phase was performed to conduct the experiment and validate or disprove the hypothesis made followed by an evaluation of the test-result. Thereafter, settings and conditions were adjusted based on experience from the previously performed tests to optimise the result. In total 17 exploratory tests were conducted according to this five-phase cycle, and a detailed description together with a reasoning of its specific outcome is found in Appendix A.

### 3.2.1 Software settings for machine learning

All tests were performed by developing a new independent AI vision model using the ML software *AutoML* [44]. A detailed procedure of how the AI vision models were built and used is found in Figure 5. Supervised learning through single label classification was used, as the purpose of the study was to detect assembly deviations (e.g., classify if the object is in either different Insertion states or Alignment state as well as Aligned or Not aligned). *AutoML* provided the user with a suggestion of time for ML in their own time unit, *Node hours*. However, manual regulation of the number of *Node hours* assigned for ML was allowed.

Two types of data storage for the raw data were tested, *Cloud* and *Edge*. *Cloud* storage used *AutoML's* inhouse storage and was limited to online usage, while *Edge* storage offered offline usage. Moreover, every model was designed to understand the behaviour of the system during various setups as well as different degrees of ML accuracy (i.e., how precise the prediction should be after ML). All images were taken manually, and the number of images was elaborated widely from having fewer than 100 images per label up to over 1000 each. The recommendation by *AutoML* guide of using approximately 1000 images for each label was also tried [44].

After building a model, a validation using 100 untrained images, as input data, from the same setup was conducted. In addition to the external validation, the software automatically performed a validation of 10% of the images that were assigned to the model with regard to precision and recall. A high precision model produces fewer false positives, and a high recall model produces fewer false negatives. The evaluation of the model was followed by external improvement through adjustments of each factor. It was, however, not possible to continue the ML of the model after receiving the Evaluation. The ML process had to be restarted for each optimisation. The false positive and false negative results from output data could not be automatically brought back to the ML loop again.

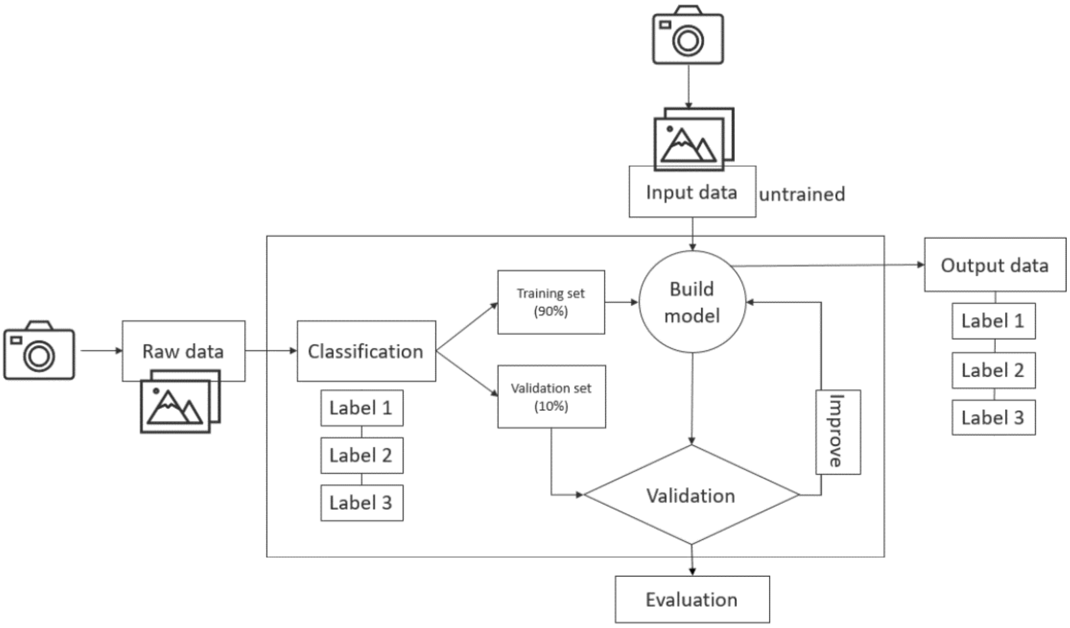


**Figure 5**. *ML process according to AutoML*

### 3.2.2 Camera setup

The camera *Logitech c922 pro hd stream webcam* and the accompanying software *Logitech Capture* allowed manual adjustment of a few image settings: Zoom, Focus, White balance, Brightness, Sharpness, Contrast and Saturation [45]. These were among the factors selected to be further investigated. During the testing all image settings were adjusted manually, optimised, and gradually locked into a standard setup. This was because the company requested trying to minimise the setup time for implementation of the AI vision system. It was suggested early by the company that usage of monochrome settings could detect objects more accurately. Therefore, this image setting was introduced after a few tests and Brightness, Saturation and White balance were locked accordingly. The settings for Contrast and Sharpness were thereafter optimised to fit the previously mentioned locked settings. However, the Zoom and Focus function were modified for every test.

The position of the camera was studied in three dimensions, see Figure 6. These dimensions were important to evaluate in order to determine the most appropriate position for the camera. The first dimension, distance between the camera and object, increased stepwise from 10 cm to 100 cm. The other dimension, camera height, was optimised for each test to fully visualise objects from an orthogonal view. The third dimension evaluated was horizontal camera direction relative to the object. The dimension was changed horizontally to investigate various angles to capture the objects.

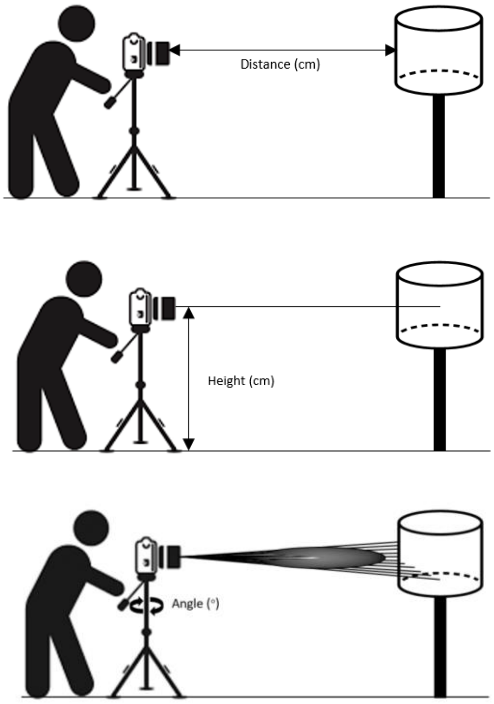


**Figure 6**. *The camera positions in three dimesons*

### 3.2.3 Environmental factors

The chosen environmental factors were inspired from a manufacturing environment and the location where the images for raw data to ML were taken. The first few tests were performed with uncontrolled disturbances behind the object (i.e., a standard manufacturing environment). Thereafter, all disturbances were removed, and the system was trained to capture an isolated object using a white background. Gradually, a more detailed but standardised background was implemented. Moreover, the location of ML with regard to the intended location for practice was evaluated. Changes of location were made to practise the AI vision in various setups. Two locations were used to collect images for raw data, a testing place at the office and a workstation disconnected from main line at the plant. A few tests were also performed to simulate a moving line setup but primarily the testing was conducted using a stationary line setup. Illumination, the last environmental factor, was increased using a flashlight.

### 3.2.4 Objects to detect

The company suggested four different suitable types of objects to evaluate the functionality of the AI vision system: Screw, Contact, Connector and Clamp. These objects were further divided into binary and complex objects, with regard to their number of states of incorrect mounting (i.e., several Insertion states for complex objects and Not aligned state for binary objects). All objects were evaluated separately. The company requested evaluating up to three objects at the same time. Hence, the number of objects to detect at the same time increased gradually from one to three. Different positions and combinations of objects were also studied to understand whether and how the AI vision was affected by capturing several objects at the same time. Furthermore, various colouring of objects and background were tested. As there was a limited number of objects available for ML, only one setup of objects was used (e.g., the same three clamps were used for ML and these were not switched).

## 3.3 Robustness test

The robustness test was performed to understand the system’s behaviour during changes of the impactful factors with regard to precision and recall. The system’s sensitivity relative to changes was of interest to ensure reliability before the final test. In addition, it was of interest to determine if the raw data for ML could be gathered at an isolated workstation disconnected from an actual production line and thereafter practiced at the intended workstation. This was to avoid unnecessary disturbance of production during implementation. At first, a concretisation of Design of Experiment (DOE) was made using the software JMP [46]. The process of creating a DOE contained five stages [47]. A detailed description of these five stages can be found in Table 1.

**Table 1.** *The process of Design of Experiment (DOE)*

| Stages | | Description |
|---|---|---|
| 1 | Set objectives | Objectives had to be formulated to establish the purpose and outcome of the test. A screening design was chosen to identify the significant factors with regard to precision and recall of the AI vision. |
| 2 | Selection of factors | The factors selected were the impactful factors that required further evaluation. For each factor selected, appropriate factor levels had to be determined. The factors were then categorised in two or three levels: lower, middle and upper. Together, the upper and lower level constituted boundaries for a process window for each factor. Furthermore, the factors were considered as categorical within JMP. |
| 3 | Select an experimental design | A selection of experimental design had to be made. As there were more than five factors to further investigate, recommendations were made to use a costum design [47]. This was based on modified factorial evaluation since there were only categorical variables within the model. |
| 4 | Execute the design of the experiment | The software JMP provided a DOE with 140 recommended runs (see, Appendix B). Every run contained a combination of the factors at respective factor level. The different settings for each run were performed strictly in accordance with the instructions. One image was taken manually for every run. An AI vision model was built following the procedure from Figure 5. The setup used can be seen in Appendix C. |
| 5 | Evaluation | Thereafter, the taken images for each run were evaluated with regard to precision and recall, see Appendix C. A screening process was applied to evaluate the factors' impact. |

As described in Table 1, the main intention of the test was to determine the significant factors for the AI vision. The selected factors that required further evaluation were: all the ten settings for camera setup, position of the object as well as the two environmental differences (background disturbances and illumination). Every setting within the camera setup was selected for the test because validation of the standard settings established during earlier testing was important. Moreover, the position of the object required further evaluation to determine how to capture the object in the best possible way. Additional background disturbances and illumination were chosen as well since there was a high probability that these would change uncontrollably during the usage of the AI vision. The additional background disturbances consisted of a label and a tube placed close to the objects as these items were expected disturbances within manufacture environment by the company.

The factors were considered categorical, each with two or three levels, see Table 1. The entire set up used for ML is found in Appendix C and the procedure followed for ML is illustrated in Figure 5. The chosen process window for each of the selected impactful factors is shown in Table 2.

**Table 2**. *Process window for each of the selected impactful factors*

| Factor | Factor Level<br>LOWER BOUNDARY | <br>MIDDLE | <br>UPPER BOUNDARY |
|---|---|---|---|
| Illumination | Not of Value | Standard | Brighter |
| Background disturbance | Not of Value | NO | YES |
| Position of object | Left | Middle | Right |
| Camera height | 104 cm | 109 cm | 114 cm |
| Camera angle towards the object | 72° (-18° to the right) | 90° | 108° (+18° to the left) |
| Distance between camera and object | 95 cm | 100 cm | 105 cm |
| Zoom | 351% | 372% | 394% |
| Focus | 0 | 4 | 8 |
| Brightness | 106 | 125 | 144 |
| Sharpness | 99 | 125 | 147 |
| Contrast | 97 | 123 | 148 |
| Saturation | 0 | 11 | 21 |
| White balance | 4340 | 5425 | 6510 |

An additional external validation of the built model was also made with 100 untrained images using the trained setup. As mentioned earlier a limited number of objects could be used for ML and only one setup of the objects was used, see Section 3.2.4. Furthermore, the object type selected was binary and three clamps at different positions with four combinations were used, see Figure 7.

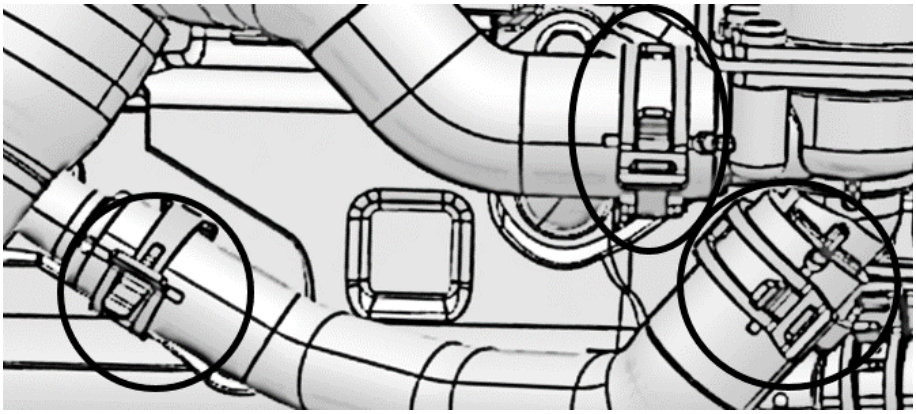


**Figure 7.** *The three clamps and their positions used for the robustness test*

The JMP software thereafter proposed 140 runs containing different combinations of setups which were strictly conducted according to Appendix C. The changes between the different runs required long time and the test was conducted for 14 hours consecutively. The test was therefore also evaluated to establish that this method of execution did not affect the test-result negatively. A screening process was thereafter performed through JMP and those factors with significant impact for the AI vision with regard to precision and recall were revealed. Notably correlations were also studied to gain a greater understanding of the system's functionality, e.g., sensitivity relative to changes. Lastly, a recommended setup for implementing an AI vision was formulated for the final test.

## 3.4 Final test in manufacturing environment

The final test was performed to validate or disprove the ML setup developed and based on conclusions from former testing. The concluded ML setup addressed is found in Table 3.

**Table 3.** *The concluded ML setup addressed for the final test*

| Area | Factor | Setup |
|---|---|---|
| Environmental setup | Location for ML | At the intended position |
| | Line setup | Stationary line setup |
| | Illumination | Standard |
| | Background disturbances | Standardised |
| Software settings for machine learning | Label classification | Single Label classification |
| | Storage | Cloud Storage |
| | Training accuracy | High accuracy |
| | Number of images per label | 900 |
| | Time for ML | 16 *Node hours* |
| | Number of labels | 2 |
| Camera setup | Camera height | 110 cm (fully visualisation of the object) |
| | Camera angle relative to the object | Orthogonal view (90°) |
| | Distance between camera and object | 100cm |
| | Zoom | 399 |
| | Focus | 0 |
| | Brightness | 125 |
| | Sharpness | 125 |
| | Contrast | 123 |
| | Saturation | 0 |
| | White balance | 5425 |
| Object to detect | Type of object | Binary (Clamp) |
| | Position of object | Centralised in the middle |
| | Number of Objects to detect | 1 |
| | Colour of object | Chrome (different from background) |

The chosen test object was one Clamp mounted in the middle of the product. The image settings, described in Table 3, produced a monochrome setup. All images were taken manually. The camera was positioned to centralise the clamp in the image and to receive an orthogonal view relative to the clamp. The centralising was eased by using the Grid function that was offered in *Capture Logitech*. The software settings for ML that were concluded during the exploratory testing were set accordingly. The test focused on the AI vision's ability to detect quality deviations in a manufacturing environment. Hence, the test was conducted at a manual assembly line at final stage. The final test was performed for two days consecutively, one day for gathering raw data for ML and one day for conducting the test. The first day ML was performed stationary at the intended workstation. The procedure used for ML is found in Figure 5. The second day the test was conducted during both moving and stationary line setup according to the case company's request. To ease the testing of stationary line setup, some small stops were performed at the moving line. An illustration of the setup at the workstation used for both ML and test is found in Figure 8.

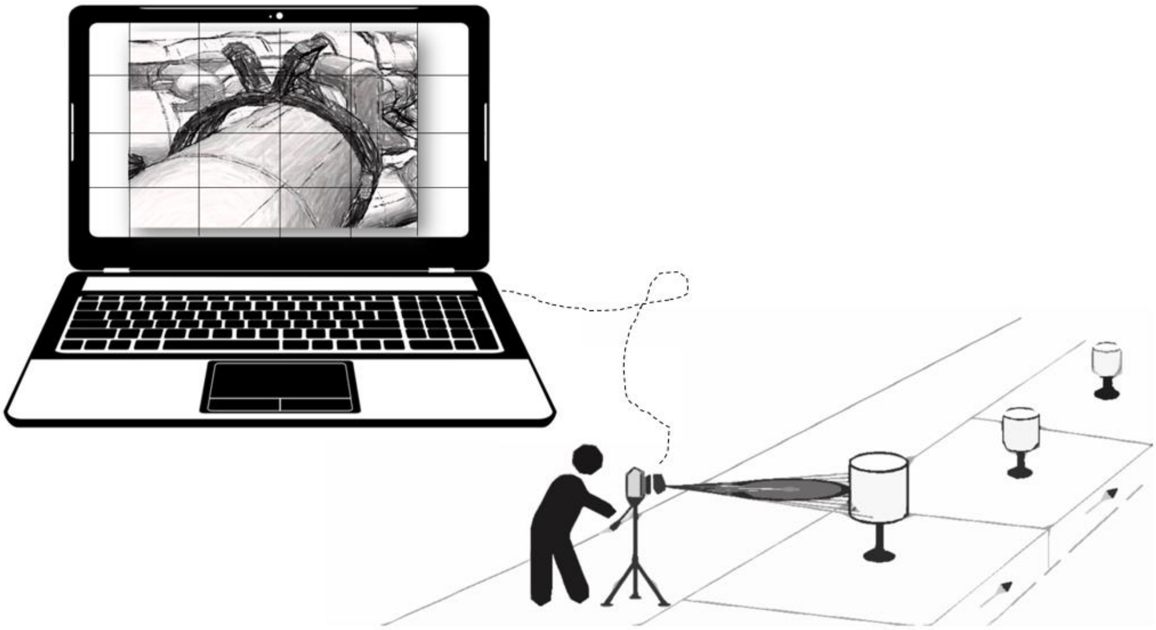


**Figure 8**. An illustration of both ML and test for the final test

In total, the test consisted of inspecting a sample of 200 clamps, each mounted on a product. As there were more than one product variant at the line, the chosen clamp for the testing was positioned at the same place on both products. These products were addressed as Product A and Product B. The AI vision was only taught to detect the clamp on Product A. Moreover, the products followed a sequence at the moving line and were therefore distributed accordingly without any prior notice. During the test the distribution of errors was random.

# 4 Result

The following chapter presents the results from the entire case study. This chapter is divided into four subsections. The first subsection provides an overview of the observations made at the company regarding their quality management. Thereafter, the identified impactful factors from the exploratory testing are presented. The findings from the robustness test are described in the following subsection. The last subsection presents the result of the final test performed in a manufacturing environment.

## 4.1 Current state of quality management

A very strong corporate culture that focuses on delivering products with high quality as well as striving to form a sustainable work environment for their employees was emphasised. According to the company manual assemblies are designed to eliminate any risk of incorrect assembly. A lot of different preventive strategies such as FMEA were also mentioned as a part of their process of designing an assembly solution. Moreover, it was described that their operators receive aids to perform demanding work tasks as a part of their manual assembly procedure. Examples of these aids are: specially designed tools and fixtures, kitting boxes with the correct number of assembly items and production integrated quality management systems. If problems occur the performing operator receives a signal and if the problems are not solved within a few seconds, the production line stops. Currently there are several reactive strategies to ensure quality of the products. These are shown in Table 4.

Despite these mentioned measures, extra controls sometimes are required to improve delivery of high product quality. Today, these extra controls are performed manually as the operators learn easily what to search for and could quickly be positioned at a requested location in the production process.

**Table 4.** *The currently used quality management systems at the company*

| Quality strategies | Description |
|---|---|
| Self-controls | After an operator has performed a work task, a following inspection of the task is included in the work sequence. |
| Vision systems | Vision systems that use a reference image to inspect if an item is placed correctly. |
| Controls by several operators | Independent operators controlling the assembly by marking it, these marks are thereafter controlled by a third operator at another workstation. |
| Continuous improvement | A philosophy of striving to constantly want to improve the methods used as there are no perfect methods. This is done by continuous follow-ups of the current methods. |
| Sample checks | Checking randomly selected assemblies using a control plan with a specific time interval. |
| Quality inspection stations | Additional stations assigned to check a specific assembly. |
| Scanners | Scanners that manually and automatically are used to ensure that specific items are mounted. If problems occur the performing operator receives a signal and often the production line is hindered to continue until the problem is solved. |
| Screw joint control | Screwdrivers that can detect the correct torque and angle while mounting a screw for example. If problems occur the performing operator receives a signal and often the production line is hindered to continue until the problem is solved. |

It has been established by the company that the current quality inspection method has improvement potential. The primary identified areas are the work environment for the operators and shortage of skilled operators to perform the work tasks. Another aspect mentioned was the placement of the quality inspections. The company strives to optimise the processes by detecting eventual deviations early in the process, preferably directly after mounting. This is to decrease unnecessary rework and disassembling. Furthermore, it was highlighted that optimising the production process by reducing disturbances as well as operator variability is a part of their philosophy.

As the quality management systems available at the company are integrated in the production system, these also require a long set up time and thereby also large costs. The identified gap is the lack of cost-efficient quality inspection systems that are easy to install quickly wherever needed. The company proposed that an AI vision system should have less than 1% error rate in order to avoid unnecessary interruptions during the production process.

## 4.2 The identified impactful factors

This subsection presents the identified impactful factors within each area that were established exploratorily, as shown in Figure 9. The subsection is divided as follows: Software settings for machine learning, Camera setups, Environmental factors, and the Objects to detect.

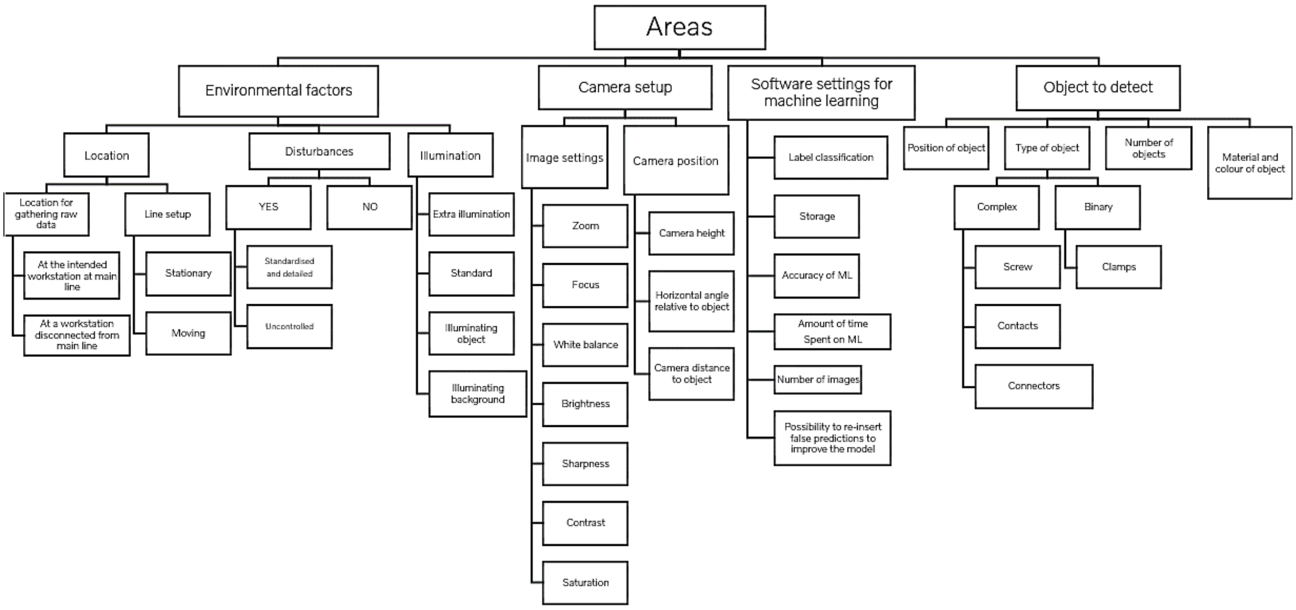


**Figure 9.** *The identified impactful factors*

### 4.2.1 Software settings for machine learning

The machine learning software *AutoML* had several settings. Six of these had a vast impact on the performance of the AI vision, see Figure 9. For example, it was shown that the number of assigned labels impacted the performance of classifying correctly. Separate labelling of every state of incorrect mounting simplified the classification since the system was trained more specifically on each state. This was evident during the testing of two contacts where all insertion states during mounting were categorised, labelled and trained separately accordingly: *A-Missing, B-missing, Both-missing,* and *None-connected,* see Test13 in Appendix A.

It was further highlighted that the choice of storage impacted the AI vision and using Cloud storage provided much lower error rate than Edge storage. However, it also required a significantly longer time for ML. Another factor that impacted the performance of precision and recall was the accuracy of ML, the higher accuracy the better. Moreover, it was found that a longer time spent on ML resulted in a more reliable model. For example, during test 11, see Appendix A, the same set of raw data was trained twofold using different number of *Node hours*. Longer ML time became significantly more reliable with the error rate 0% compared to 15%.

Raw data with a lower number of images than 500 for ML provided a poor result. However, using approximately 1000 images for each label provided a better result with regard to precision and recall. Moreover, the number of insertion states within each label affected the required number of images. For example, the contacts had many different insertion states within every label that needed to be captured. Therefore, the number of images for ML exceeded 1000, while the binary object, clamp, only needed 900 images to provide a reliable result, see Appendix A. Lastly it was identified that the system was not able to automatically re-insert the false positive and false negative images back to the ML loop again to quickly optimise the model.

### 4.2.2 Camera setup

The camera setup impacted the performance of the AI vison in many ways, see Figure 9. Monochrome settings eased the AI vision's ability to learn, detect correct objects and adapt to different test-objects. Thereby, Saturation and White balance were adjusted to achieve the monochrome setting. Moreover, as the camera was equipped with a digital zoom and not optical zoom the enlarged images were not clearly visualised. The automatic regulation of Zoom was also limited. Hence, manual control of Zoom was required for each test to clearly visualise the objects. The lack of automatic regulation of Zoom impacted the ability to apply the AI vision at a moving line setup. The image settings, Contrast, Brightness and Sharpness also impacted the possibility to clearly visualise the object. A strong relation between Zoom and Focus was identified as well. Furthermore, the image quality was [37]significantly improved by a shorter distance between the camera and the object, the closer the better, see Figure 10. This was based on observations that the Zoom function was limited, resulting in a blurry image.

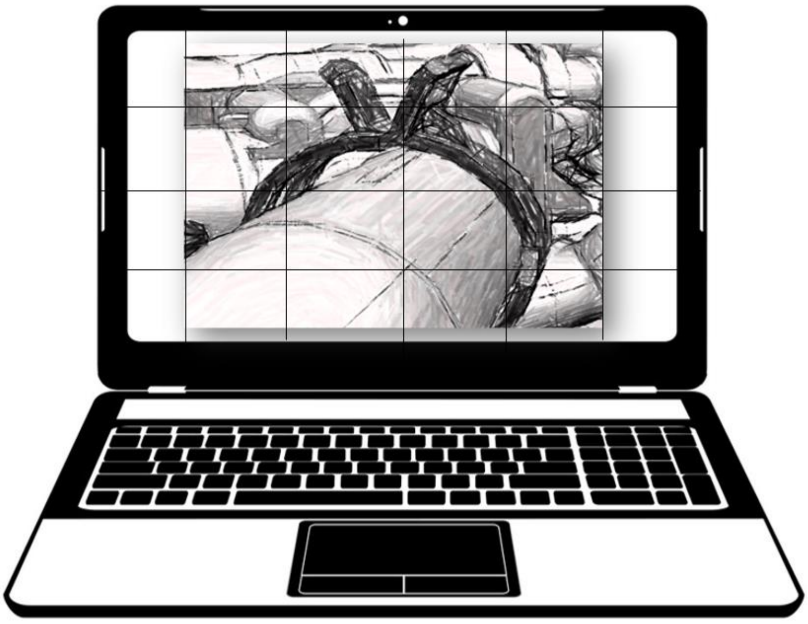


**Figure 10.** An optimised view of the object to be detected

It was also found that the camera was limited in being placed with a greater distance of 100 cm from the object. However, the expected distance to apply within the manufacturing environment was at least 100 cm because of the moving line setup. Furthermore, the camera height was important for the ability to detect objects correctly. It was determined that the camera preferably should be positioned to centralise the objects of interest. The choice of horizontal angle relative to the object was also highlighted as important. Capturing objects from an orthogonal view was most successful. The importance of how to capture objects correctly was especially clear during testing of two contacts, see Appendix A Figure 12 . The first test preformed with two contacts in a manufacturing environment, Test 14, had a large error rate. After changing the horizontal angle for capturing the object, it had 100% correct result during the external validation of untrained images, Test 16.

### 4.2.3 Environmental factors

To successfully implement an AI vision system in a manufacturing environment some additional factors needed to be considered. The factors addressed were: Disturbances, Location and Illumination setup, Figure 11. Performing ML trying to detect objects with uncontrolled background disturbances greatly impacted the result negatively. The AI vision misunderstood and became confused what to focus on. Recognising what was foreground and what was background revealed to be challenging. However, the AI vision detected several objects at the same time correctly both in various incorrect mounting states as well as in Alignment state with a standardised background. An example of standardised background is capturing objects mounted on a product.

Different illumination affected the performance of AI vision systems. For example, it was important to consider if the background or the object should be illuminated. This was especially prominent during the testing of the screw which required an illuminated background since the various insertion states of the screw then were easier to detect. Notably, having a dark screw and lightened background enabled the light from behind to be displayed. In addition, the camera's focus was impaired by shadows which made the direction of the illumination important as well. Moreover, the location site was vital during the implementation, both location for ML and line set up. A slight sensitivity towards changes of different ML environments emerged. The AI vision notedly performed negatively during movement compared to a stationary line setup.

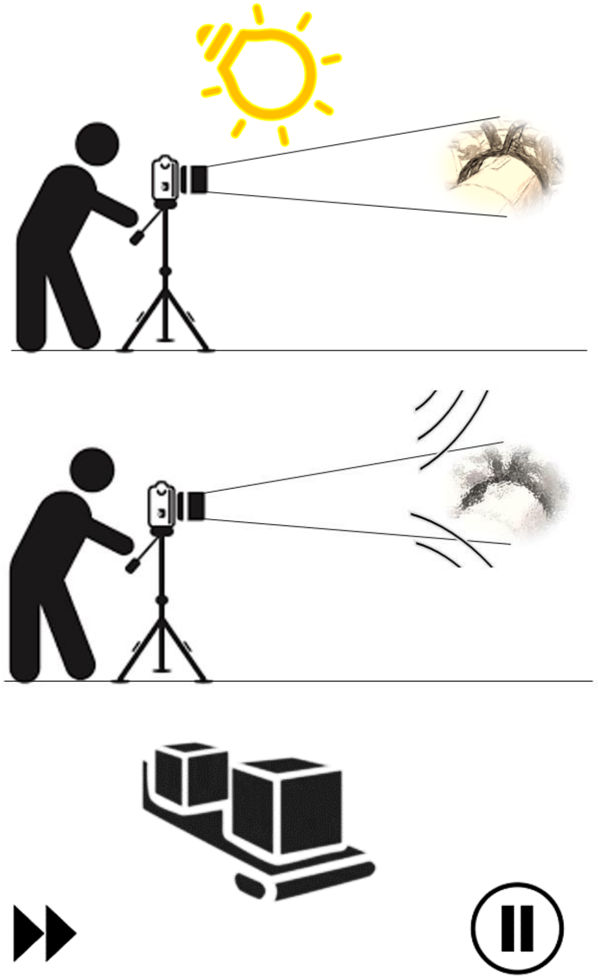


**Figure 11.** The environmental factors identified: Illumination, Disturbances and Line setup

### 4.2.4 Objects to detect

The object's level of complexity, (i.e., number of different insertion states), affected the AI vision's performance negatively. For example, the most complex object evaluated was a screw that was mounted into a plate. It appeared that many nuanced distinctions were too small to be detected by the AI vision, see Figure 12. Despite isolating the screw from any background disturbances, the system had trouble detecting non-aligned insertion states. However, the clamp, categorised as binary, was successfully detected in its two states of either closed (Aligned) or opened (Not Aligned). It was also noticed that detecting these types of objects required less setup time.

**Figure 12**. *A visualisation of Insertion state and Alignment state while mounting a screw*

The number of objects to detect at the same time was further found to impact the AI vision system's performance. Handling three objects at the same time was clearly more challenging for the system than handling one, regardless of the type of object. However, detecting three objects simultaneously during a standardised setup was successful for both clamps and connectors, respectively, see Appendix A. Capturing a clear vision of each object and its various states was crucial.

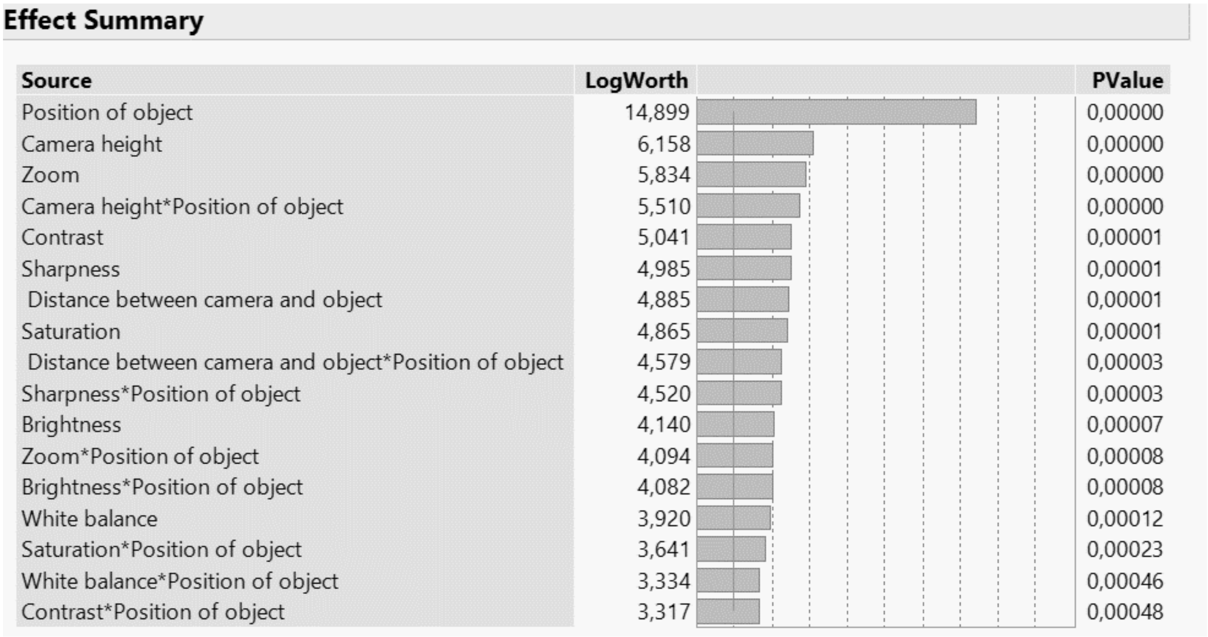
Another factor emphasised was the importance of the object's position, especially while capturing more than one object at the same time. For example, it was observed that all clamps used for the testing were pre-mounted with a tolerance of +/-10° around the tube, see Figure 13. This tolerance hindered fully capturing three clamps in their various states simultaneously. The AI vision system was however able to capture the three clamps with different combinations of opened and closed during a standardised setup.

**Figure 13.** *The Clamps' rotations around the tube*

The choice of material and colour of the object as well as the background affected the AI vision's ability to detect the object correctly. Although using monochrome setup, having the same colouring for the background and object impacted the result negatively. This was because the system had trouble with detecting some of the Not Aligned Insertion states. However, objects differently coloured from the background eased the detection of the various incorrect mounting states, especially of the complex objects. For example, a green colouring of the connectors and contacts together with a black background was beneficial for the AI vision system to capture and detect correctly.

## 4.3 The AI vision system's sensitivity to changes in setup

Teaching the AI vision during a specific setup and thereafter changing the setup, had a negative impact on the performance to detect three clamps simultaneously. A detailed description of the findings is found in Appendix D. The test showed an error rate higher than 30% for all four combinations of the three clamps that were evaluated. Thereby, during changes, the number of objects to detect seemed to have a major impact on the AI vision. Furthermore, the conducted screening process revealed the following significant factors, see Figure 14.



**Effect Summary**

| Source | LogWorth | PValue |
|---|---|---|
| Position of object | 14,899 | 0,00000 |
| Camera height | 6,158 | 0,00000 |
| Zoom | 5,834 | 0,00000 |
| Camera height*Position of object | 5,510 | 0,00000 |
| Contrast | 5,041 | 0,00001 |
| Sharpness | 4,985 | 0,00001 |
| Distance between camera and object | 4,885 | 0,00001 |
| Saturation | 4,865 | 0,00001 |
| Distance between camera and object*Position of object | 4,579 | 0,00003 |
| Sharpness*Position of object | 4,520 | 0,00003 |
| Brightness | 4,140 | 0,00007 |
| Zoom*Position of object | 4,094 | 0,00008 |
| Brightness*Position of object | 4,082 | 0,00008 |
| White balance | 3,920 | 0,00012 |
| Saturation*Position of object | 3,641 | 0,00023 |
| White balance*Position of object | 3,334 | 0,00046 |
| Contrast*Position of object | 3,317 | 0,00048 |

* LogWorth stands for 'Size effects' and estimates the effect of the variable in the system

**Figure 14.** *Significant impactful factors – in decreasing order*

The position of object was the most significant factor for the AI vision system. It was clear that centralising the clamp (i.e., placing the clamp in the middle, see Figure 7 in Section 3.3) resulted in increased performance regardless of different settings. The few errors for the middle clamp occurred because of added background disturbances. Generally, the other two positions studied had a lower performance during changed setup. In contrast to the middle clamp, a clear negative effect of the added background disturbance was not identified for the outer two positions. Moreover, additional illumination increased the system's ability to perform accurately.

The changes of camera height impacted the visualisation of the clamps. Having the clamp positioned in the middle at the same height as during ML provided the best performance. It was also revealed that the middle position was more robust towards the changes of camera height compared to the other two. Positioning the camera with a shorter distance to the clamp in the middle significantly improved the result. A clear pattern was identified as well, the error rate increased with increased distance. This pattern, however, was not characteristic for the other two positions as the error rates were evenly distributed between the distances.

The clamp placed in the middle had the best performance regardless the changes of Zoom. The test also showed that trying to select as high a value as possible on the camera's Zoom function resulted in. improved performance. In addition, an interplay between Focus, Zoom and distance between camera and object was identified. For example, an increased distance between the camera and object required a higher setting of Zoom and a lower setting of Focus. Selecting the highest value of Focus and Zoom in combination with the lowest distance between camera and object was reliable as no errors occurred for the middle clamp.

The choice of Sharpness setting used for ML setup was clearly shown to be most accommodating for the clamp placed in the middle and contributing to the best performance. It was also clear that the clamp placed in the middle had lower error rate within the process window than the outer two. Furthermore, a higher setting of Brightness than used during ML setup increased the performance. The Contrast was the last camera setting evaluated with significant impact. It was noted that changing the Contrast within the selected process window impacted the error rate very little.

## 4.4 The final test in a manufacturing environment

The model built to be evaluated during the final test of detecting one clamp showed high recall and precision as no errors during ML validation occurred, see Appendix E Figure 1. Despite these indications of a reliable model, the AI vision only predicted 47% (94/200) correctly during practice, see Figure 15.

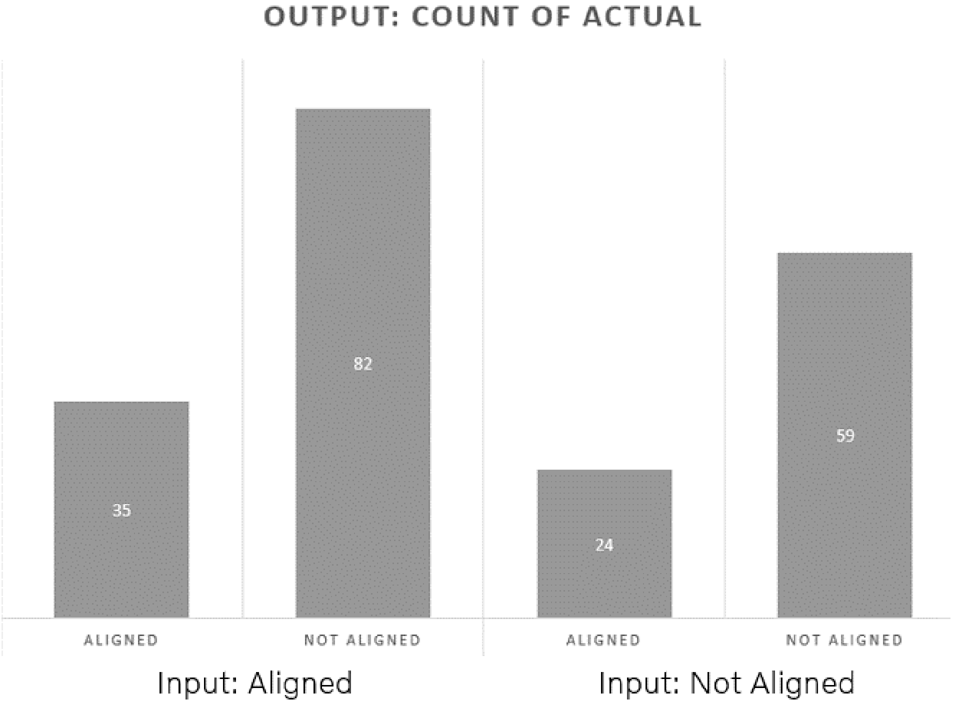


**Figure 15.** *The result of the final test*

Aligned state seemed to be the most challenging state to detect, 70,1% (82/117) errors occurred. Among these the majority, 61% (50/82), were in a stationary line setup. Not aligned state, however, had fewer errors than correct predictions, 28,9% (24/83). Moreover, it was shown that only 29,4% (5/17) of the number of Product B were correctly predicted. Product A had a more even distribution between correct and wrong, 48,6% (89/183) respectively 52,4% (94/183). It was further identified that the stationary line setup contributed to a higher number of incorrect predictions (70 wrong, 57 correct) while the moving line setup had an even distribution of correct and wrong (36 wrong, 37 correct). Illustrations of the presented findings are found in, Appendix E.

# 5 Social and ethical aspects

Improvements of the current quality inspection method of product deviations could increase product quality as well as contribute to better market competitiveness. Implementing a cost-efficient and approachable AI vision has the potential to easily detect errors in manual assembly. It could also improve the assemblers' work environment by reducing demanding work tasks as well as the resulting costs [16]. Changes such as implementing technical solutions to reduce costs and optimising production processes can arouse fear of unemployment among the assemblers [32]. The fear of not performing a job well enough and being limited in influencing the work situation could result in a reduced motivation towards work [28]. To be able to perform well at work, it is required that the assemblers feel workflow and professional pride [1].

AI vision could preferably be used to perform monotonous or unsafe work and tasks with very tight tolerance [32]. Although, it has been established that AI vision handles certain tasks better than humans, the AI vision cannot override human ability. Experiences of being replaced instead of mitigating workload needs to be avoided. Hence, the implementation of AI vision needs to take into account both the aspects of improving product quality as well as acceptance from the assemblers towards changes. For example, it is important to convey the purpose of implementing AI vision and to highlight that restructuring of work tasks is in progress. This could be done through applying Lean manufacturing strategy that entails having the right person on the right place at the right time [39]. By motivating changes accordingly, a focus on establishing a sustainable work environment could be achieved.

# 6 Discussion

The exploratory testing conducted at a workstation disconnected from main line (i.e., with a standardised background and conditions, without any additional disturbances) provided a very reliable result for the AI vision. The system managed to detect up to three clamps simultaneously with various positions at the product as well as two connectors with more than one insertion state to detect. The precision and recall were 100% even with detailed but standardised background both during validation and practice. Therefore, the transition to a manufacturing environment felt natural. However, during the final test at a workstation at main line the AI vision system's performance decreased considerably. Only 47% of the images were correctly predicted. It was established during exploratory testing as well as the robustness test that the system showed a tendency of being sensitive towards changes. Hence, the final result was not unexpected. This could be because the numerous uncontrolled disturbances in the manufacturing environment were not possible to replicate during the exploratory testing. For example, there were performing assemblers close to the setup of the AI vision system and the illumination varied.

Regarding camera setup, it was already known that the expected distance between camera and object was at least 100 cm at a moving line setup. It was also known that this distance was a hinder for the camera, as both the exploratory testing and robustness test revealed that a shorter distance provided a better result. This could be because a shorter distance would imply a more homogeneous background and reduce the distractions - making it easier to discriminate vital deviations from uncontrolled deviations. In addition, the digital zoom made it challenging to clearly visualise the objects at this distance. Having an optical zoom could have eased detection by enlarging the object of interest, thereby reducing disturbing details in the image while maintaining a clear vision of the object. The interplay between Focus and Zoom and distance between camera and object was also of importance. The setting for Zoom and Focus needed to be optimised to accompany the chosen distance. It could therefore be emphasised that the placement of the AI vision needed to be changed.

The ML for the final test was only performed during a stationary line setup at the intended workstation. However, this choice could have affected the result negatively as the AI vision was not taught to detect the clamp during moving line setup. In addition, only one of the two products, Product A, was included during ML which resulted in a higher error rate. The high error rate could be because the clamp’s background then consisted of two different products with small but disturbing distinctions. Moreover, the limited number of clamps available for raw data to the ML could have affected the result negatively - mainly because the small variance between the clamps was diminished during ML compared to practice. Another important contributing factor to consider is the tolerance of the position of the clamp assigned. This was because the ML for the final test was performed with the same product and not with several similar products. It was not possible to know in which of the positions within the tolerance the chosen clamp for ML had. Thereby, the AI vision was not taught to detect all possible changes of the position of the clamp around the tube.

Performing ML one day and the final test the other day might have impacted the result negatively as the setup had to be done twice and it was already known that the system was very sensitive towards changes. Moreover, images were taken manually which could have affected the ability to capture the product correctly. Lastly, *AutoML* was limited in re-inserting the input images that were predicted as false positive and false negative. A new model had to be created instead of improving the already existing, slowing down the optimisation of the model. The ML platform also has potential for development to ease optimisation of the model by introducing a loop back to the raw data. This loop would imply an easy way back to the ML-loop without any manual effort to further optimise the AI vision model.

# 7 Conclusion

The implementation of AI vision to detect incorrect assembly could improve the product quality directly during the manufacturing process and help ensure that customers do not receive imperfect products. During the study it was identified that the current state of the suggested AI vision system was suitable for detecting binary problems e.g., [Opened, Closed] or [True, False]. It was also shown that colouring the object differently from the background eased detection.

It was revealed that the distance between the camera and object significantly impacted the AI vision system’s possibility to accurately detect objects in a manufacturing environment. A shorter distance eased the detection significantly and this was mostly because of the camera’s Zoom function (digital zoom) that was limited in clearly visualising the object at a greater distance. There was also a strong interplay between Zoom, Focus and the distance between camera and the object. Since the camera’s Zoom and Focus functions were insufficient, distance became crucial. Moreover, all testing showed that additional background disturbances impacted the AI vision’s performance negatively. The camera was sufficient during a standardised background but not at the final test at the moving line setup. The position of object was also considered a very important factor according to the robustness test. It was identified that non-central placement of the object increased the AI vision’s sensitivity towards all changes. It was further found that capturing the object from a non- orthogonal angle limited the AI vision system’s possibility to detect the deviations correctly and the object should be captured centralised from an orthogonal view.

Foremost it was concluded that gathering raw data for ML at the intended workstation, using the same setup and position as during practice, was of importance for a lower error rate. The ML process was for example eased by using monochrome settings as the deviations were more clearly visualised. It was also highlighted that the system was affected by the number of images used for raw data. Approximately 1000 images for each label were suitable. In addition, when possible, classifying the images into more labels than correct and incorrect eased the ML ability for the AI vision. For example, classifying the different incorrect mounting states into each separate label was a successful strategy as the AI vision then received more images for each state. Moreover, the number of objects to detect at the same time also affected the ML process as detecting a larger number of objects simultaneously was more challenging for the system than detecting only one.

Image quality had a vast impact on ML, making it important to optimise the setup for gathering raw data images. The time spent on ML as well as the number of images was also vital for the ML result. The lack of possibility to re-insert the input images that were predicted false positive and false negative created a longer time for optimisation of AI vision model. Such a re-insertion of false predicted images could quickly improve the model after validation by immediately improving the already existing model.

The company proposed that an AI vision system should have less than 1% error rate in order to be satisfactory, and to avoid unnecessary interruptions during the production process. This goal was not accomplished during this study and the given hardware. However, a further evaluation of the current AI vision system within a manufacturing environment is suggested, trying to optimise the settings and reach the company’s request.

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# Appendix A

The following appendix contains a description of the tests performed during the exploratory testing and its outcomes.

**Common for all tests:**

- 100 untrained images were used to verify the model in addition to the AutoML's evaluation with regard to Precision and Recall.
- NOK stands for 'Not Okay' assembly
- OK stands for 'Okay' assembly

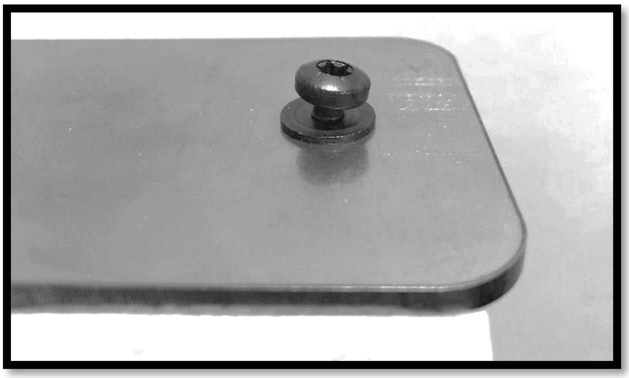
**Test 1-2** were performed to become acquainted with both the camera as well as the software. The test used 200 images for ML which required one *Node hours*. The model had two labels, and there were more images in NOK-label than OK-label because there were several incorrect mounting states in NOK-label. A screw mounted into a plate was used as test object. The camera used colour and was placed approximately 15 cm from the screw. There were no adjustments of environmental factors such as disturbances (various background disturbances). Manual focus, Mid-accuracy for ML, Edge-storage and Single-Label Classification were used.

**Outcome**: Having distracting objects in the background decreased the result. Precision and Recall during AutoML's evaluation were less than 96%.

**Appendix A Figure 1.** *Test 1-2 where a screw was inserted into a plate*

**Test 3-4** were performed to evaluate the number of images for ML and to try understanding the environmental impact. The test used 200 images for ML which required one resp. two *Node hours*. The model had two labels, and there were equal number of images in NOK-label and OK-label as the difference number of images in the labels could impact the result. A screw mounted into a plate was used as test object. The camera used colour and was placed approximately 20 cm from the screw. The object was placed within an isolated environment. Manual focus, High-accuracy for ML, Edge-storage, and Single-Label classification were used.

**Outcome**: Having 200 images for ML were not enough to get a reliable result and having an increased time for ML did not affect the result positively. Precision and Recall during AutoML's evaluation decreased to less than 90%.



**Appendix A Figure 2.** *Test 3-4 where a screw was inserted into a plate*

**Test 5-7** were performed to further evaluate the number of images for ML. The test increased the number of images for ML each test to evaluate its impact. Different number of *Node hours* were used for ML. The model had two labels. There were more images in NOK-label than OK-label because of the several options of incorrect mounting states in NOK-label. The NOK-label had 50% more images than OK-label. A screw mounted into a plate was used as test object. The camera used colour and was placed approximately 10 cm from the screw. The screw was placed isolated and there were no disturbances. Manual focus, High-accuracy for ML, Edge-storage, and Single-Label Classification were used.

**Outcome**: Having more than 200 and maximum 900 images for ML was not enough to get a reliable result. The increased time for ML did not affect the result positively. Precision and Recall during AutoML's evaluation varied between the tests and was not improved by increased number of images for ML. The number of different incorrect mounting and angles affected the test-result i.e., the screws complexity.

**Appendix A Figure 3.** *Test 5-7 where a screw was inserted into a plate*

**Test 8** was performed to detect if the complexity of the object impacted the result, therefore only one NOK-setup was used. The test used 170 images for ML for five *Node hours*. The model had two labels, and there were more images in OK-label than NOK-label. NOK-label only contained missing screw. A screw mounted into a plate was used as test object. The camera used colour and was placed approximately 25 cm from the screw. There were no disturbances. Additional illumination was included to assist capturing the different states of incorrect mounting. Manual focus, High-accuracy for ML, Edge-storage, and Single-Label Classification were used.

**Outcome**: Precision and Recall during *AutoML's* evaluation became 100%. Having fewer states of NOK improved the model significantly.  Thus, the complexity of the object impacts the result severely.

**Appendix A Figure 4.** *Test 8 where a screw was inserted into a plate*

**Test 9** was performed to re-expand the complexity and continue to eliminate the environmental factors. The test used 424 images for ML for five *Node hours*. The model had two labels. There were more images in NOK-label than OK-label because the number of NOK states was increased compared to test 8. The too complex incorrect mounting states were still eliminated. A screw mounted into a plate was used as test object. The camera used colour and was placed approximately 10 cm from the screw. There were no environmental factors added and there was extra illumination. Manual focus, High-accuracy for ML, Edge-storage and Single-Label Classification were used.

**Outcome**: Expanding the dataset for ML but still eliminating the too complexed incorrect mounting states was successful. Precision and Recall during *AutoML's* evaluation reached 100%. The complex incorrect mounting states were hard to detected by the camera. The differences were not able to be captured. It could be because of shadows or the insufficient illumination.

**Appendix A Figure 5.** *Test 9 where a screw was inserted into a plate*

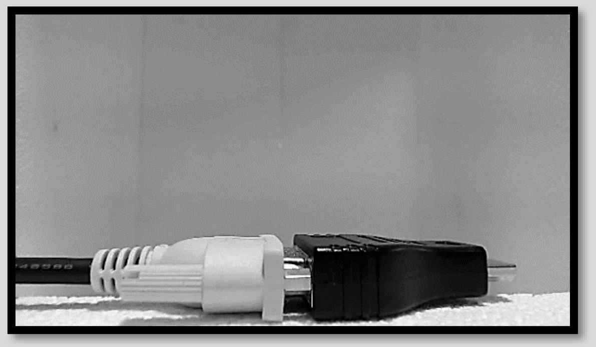
**Test 10** was performed to evaluate the possibility of using a wider range of complexity and follow some recommended setups. The test used 2050 images for ML for 16 *Node hours*. Two labels were used OK and NOK. The choice of having more than 1000 images per label was based on recommendations from the *AutoML*-platform. As problems with detecting complex incorrect mounting states were noted, a change of the illumination was done to ease detection. A screw mounted into a plate was used as test object. The camera used colour and was placed approximately 30 cm from the Screw. The screw was totally isolated. Manual focus, High-accuracy for ML, Cloud-storage, and Single-Label Classification were used.

**Outcome**: By implementing the recommended setup, a more reliable result was achieved. The precision and recall from the *AutoML* evaluation remained 100%. Cloud storage increased the required time for ML. Illumination was helpful to detect the different incorrect mounted states.

**Appendix A Figure 6**. *Test 10 where a screw was inserted into a plate*

**Test 11** was performed to explore another test-object. The test was also used to evaluate the time for ML. The test used 2150 images to for ML. Two different models were created with the same raw data set, however the ML time differed between the two tests. The model had two labels, NOK and OK. A contact was used as test object, in both standing and lying position. The camera used colour and was placed approximately 30 cm from the contact. Isolated environment was used. Manual focus, High-accuracy for ML, Cloud-storage for one of the tests and Edge-storage for the other and Single-Label Classification were used.

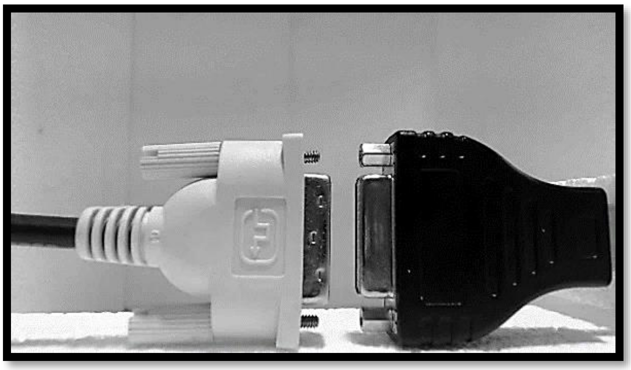
**Outcome**: Having less ML-time decreased the precision and recall. ML time for 2 *Node hours* had 85% precision and recall during evaluation, while ML time for 16 *Node hours* had a precision and recall of 100%. Conclusion of continue using Cloud-storage (that requested longer ML time) was made. Having more than 1000-images per label was also concluded as successful. The complexity of the contact was not as large as using a screw.



**Appendix A Figure 7.** *Test 11 where a contact was used*

**Test 12** was performed to evaluate possibility to use several labels for the incorrect mounting states. This was to introduce more precise detection of all incorrect mounting states. The test used 5332 images for ML for 40 *Node hours*. The model had five labels, and each label had more than 1000 images. The following labels were used; *AB-Connected*, *A-Missing, B-missing, Both-missing*, and *None-connected*. A contact was used as test object, both standing and lying position. The camera used colour and was placed approximately 20 cm from the contact. The contact was placed isolated from any environmental disturbances. Manual focus, High-accuracy for ML, Cloud-storage, and Single-Label Classification were used.

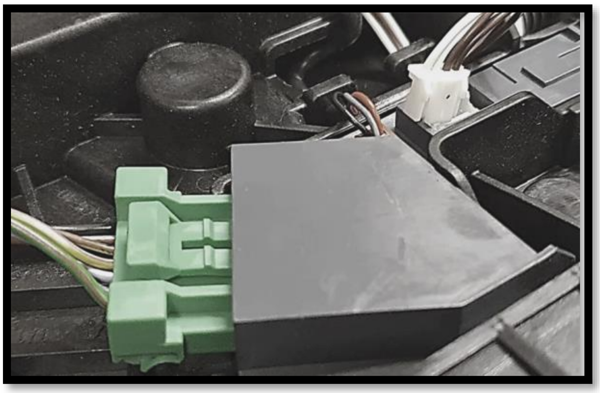
**Outcome**: Precision and recall during AutoML's evaluation was 100% and the using different labels seemed to ease the ML as there were more images for each state.



**Appendix A Figure 8.** *Test 12 where a contact was used*

**Test 13** was performed to re-instate a more manufacturing like environment and a standardised but detailed environment was introduced. In addition, the test evaluated the zooming function, expanded to two contacts, and continued to use multi-labels. The test used 4613 images for ML for 32 *Node hours.* This test introduced the recommendation of monochromous setup to ease the detection of deviations. Two contacts integrated on a product was used as test-object. The following five labels were used; *AB-Connected*, *A-Missing, B-missing, Both-missing,* and *None-connected*. The camera was placed approximately 30 cm from the contact. Manual focus, High-accuracy for ML, Cloud-storage, and Single-Label Classification were used.

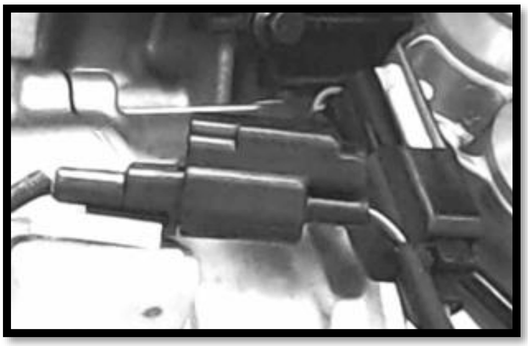
**Outcome**: According to the *AutoML's* evaluation precision and recall were 100%. A standardised but detailed environment did not impact the result negatively. The different colours on the contacts might have impacted the result positively despite the monochrome setting.



**Appendix A Figure 9.** *Test 13 where two contacts were used*

**Test 14** was performed to practice in a manufacturing environment when trying to detect two objects and continue with multi-labels. The camera settings also started to be locked as a standard setup was of interest. The test used 6000 images for ML for 40 *Node hours*. The model had four labels with 1500 images per label. The labels were named: *AB-Connected*, *A-Missing, B-missing* and *None-connected*. Two contacts were used as test objects. The camera used monochrome setup and was placed approximately 90 cm from the object. Manual focus, High-accuracy for ML, Cloud-storage and Single-Label Classification were used. Image setup: Zoom (365), Focus (13), White balance (4450), Brightness (125), Contrast (123), Sharpness (125) and Saturation (5).

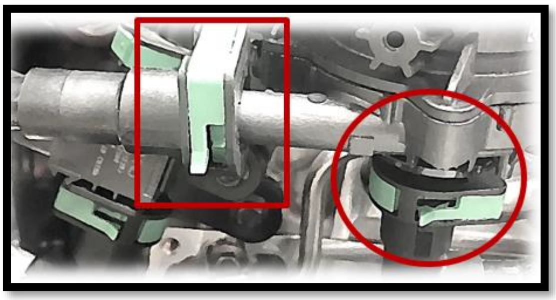
**Outcome**: The precision and recall at the *AutoML's* evaluation became 100%, however the verification of the model was unsuccessful because all images received the same label. The contacts might have been captured wrongly by the camera. Another reason for could be that the contacts had the same colour as the background. Therefore, a re-test is suggested to re-adjust the setup of the camera. The fixed camera settings worked okay. However, some adjustments of Zoom and Focus could be done as these are highly connected to the distance to the object.



**Appendix A Figure 10.** *Test 14 where two contacts were used*

**Test 15** was performed to continue practice in a manufacturing environment and further evaluating locking the camera settings. In addition, the model was verified by images with other image setups than used for ML. The test used 3600 images for ML for 32 *Node hours*. Two connectors were used as test objects. The model had four labels with 900 images per label. The following labels were used: *AB-Connected*, *A-Missing*, *B-missing*, and *None-connected*. The camera used monochrome setup and was placed approximately 95 cm from the object. The connectors were green with a black background. Manual focus, High-accuracy for ML, Cloud-storage, and Single-Label Classification were used. Image setup: Zoom (377), Focus (15), White balance (4417), Brightness (125), Contrast (123), Sharpness (125) and Saturation (16).

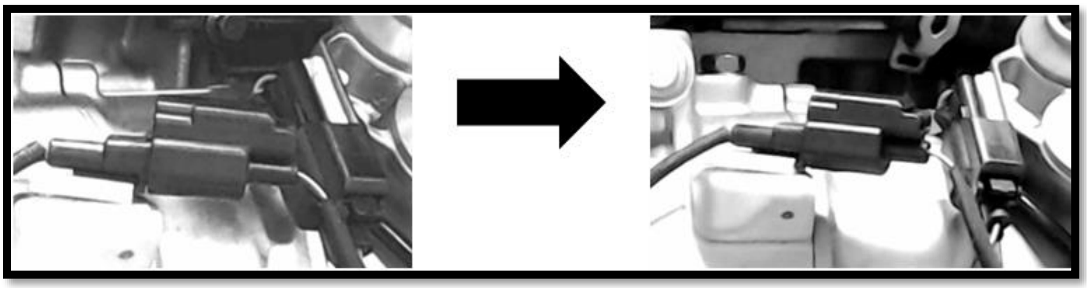
**Outcome**: The precision and recall for evaluation became 100% and the colour of the connectors might have eased detection. The detailed and standardised background did not affect the test-result negatively. The image setup worked better. However, some improvement of Zoom and Focus could be done to accommodate the distance.



**Appendix A Figure 11.** *Test 15 where two connectors were use*

**Test 16** was performed to improve the image settings used for test 14. The test continued to practice in a manufacturing environment. The test used 2000 images for ML for 16 *Node hours*. The model had two labels with 1000 images each. The name of the labels was *Connected* and *Not connected.* One of the contacts from test 14 was selected as test object. The camera used monochrome setup and was placed approximately 100 cm from the object. Manual focus, High-accuracy for ML, Cloud-storage, and Single-Label Classification were used. Image setup: Zoom (372), Focus (17), White balance (4417), Brightness (125), Contrast (123), Sharpness (125) and Saturation (0).

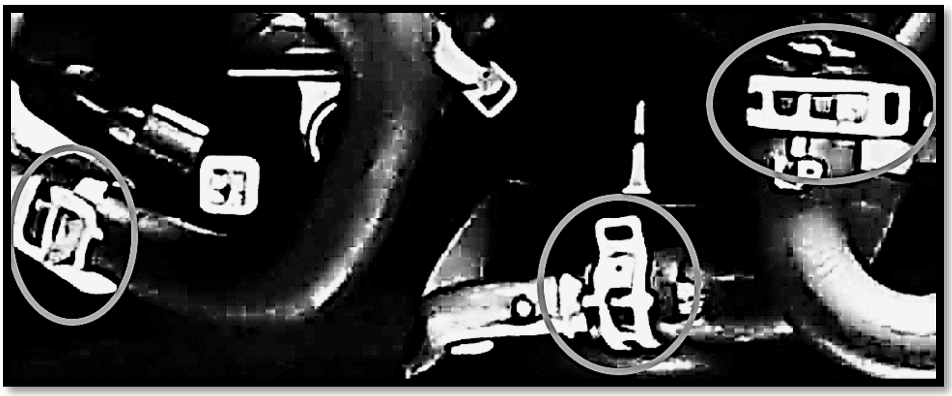
**Outcome**: The precision and recall for *AutoML* evaluation became 100%. The external valuation also had 100%. The changes of using a new angle to capture the object, a higher contrast and having less Zoom as well as only focusing on one contact is perceived to be the factors that enabled a better result. The image settings were good for the distance between the camera and the object.



**Appendix A Figure 12.** *Test 16 where the position of capturing the contact was changed*

**Test 17** was performed in a manufacturing environment, use the camera setup from test 16, and challenge the system by using three objects. The test used 7200 images for ML for 40 *Node hours*. The model had eight labels with 900 images each. Labels: *A-connected, B-connected, C-connected, AB-connected, AC-connected, BC-connected, ABC-connected* and *None-connected.* Three tube clamps in different positions were used as test objects. The camera used monochrome setup and was placed approximately 100 cm from the objects. Manual focus, High-accuracy for ML, Cloud-storage and Single-Label Classification were used. Image setup: Zoom (372), Focus (17), White balance (4417), Brightness (125), Contrast (123), Sharpness (125) and Saturation (0).

**Outcome**: The precision and recall for *AutoML's* evaluation became 100%. The external validation predicted 100%. The setup from test 16 worked well despite changing object, making them a good standard. The number of images for ML was also enough. Increasing the number of objects to detect at the same time worked successfully.



**Appendix A Figure 13.** *Test 17 where the three clamps were used*

# Appendix B

## Table of The Design of Experiment for the Robustness test and outcome

| Run | Illumination | Disturbances | Camera Horizontal angle relative to object | Camera height | Distance between camera and object | Focus | Zoom | Brightness | Sharpness | Contrast | Saturation | White balance | True combination | Predicted label | Clamp A | Clamp B | Clamp C | P-value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Standard | YES | 108 | 104 | 105 | 0 | 351 | 125 | 147 | 98 | 21 | 5425 | B connected | A connected | Wrong | Wrong | Correct | 0.513 |
| 2 | Standard | YES | 108 | 104 | 105 | 0 | 351 | 125 | 147 | 98 | 21 | 5425 | AB connected | No object | N/V | N/V | N/V | N/V |
| 3 | Standard | YES | 108 | 104 | 105 | 0 | 351 | 125 | 147 | 98 | 21 | 5425 | BC connected | BC connected | Correct | Correct | Correct | 0.582 |
| 4 | Standard | YES | 108 | 104 | 105 | 0 | 351 | 125 | 147 | 98 | 21 | 5425 | ABC connected | ABC connected | Correct | Correct | Correct | 0.945 |
| 5 | Standard | YES | 108 | 114 | 95 | 4 | 351 | 145 | 147 | 123 | 11 | 4340 | B connected | B connected | Correct | Correct | Correct | 0.698 |
| 6 | Standard | YES | 108 | 114 | 95 | 4 | 351 | 145 | 147 | 123 | 11 | 4340 | AB connected | B connected | Wrong | Correct | Correct | 0.771 |
| 7 | Standard | YES | 108 | 114 | 95 | 4 | 351 | 145 | 147 | 123 | 11 | 4340 | BC connected | ABC connected | Wrong | Correct | Correct | 0.912 |
| 8 | Standard | YES | 108 | 114 | 95 | 4 | 351 | 145 | 147 | 123 | 11 | 4340 | ABC connected | ABC connected | Correct | Correct | Correct | 0.95 |
| 9 | Standard | YES | 108 | 114 | 95 | 8 | 394 | 105 | 125 | 148 | 0 | 6500 | B connected | B connected | Correct | Correct | Correct | 0.908 |
| 10 | Standard | YES | 108 | 114 | 95 | 8 | 394 | 105 | 125 | 148 | 0 | 6500 | AB connected | BC connected | Wrong | Correct | Correct | 0.980 |
| 11 | Standard | YES | 108 | 114 | 95 | 8 | 394 | 105 | 125 | 148 | 0 | 6500 | BC connected | B connected | Correct | Correct | Wrong | 0.999 |
| 12 | Standard | YES | 108 | 114 | 95 | 8 | 394 | 105 | 125 | 148 | 0 | 6500 | ABC connected | B connected | Wrong | Correct | Wong | 0.982 |
| 13 | Standard | YES | 108 | 109 | 105 | 0 | 372 | 125 | 99 | 148 | 11 | 4340 | B connected | B connected | Correct | Correct | Correct | 0.558 |
| 14 | Standard | YES | 108 | 109 | 105 | 0 | 372 | 125 | 99 | 148 | 11 | 4340 | AB connected | B connected | Wrong | Correct | Correct | 0.996 |
| 15 | Standard | YES | 108 | 109 | 105 | 0 | 372 | 125 | 99 | 148 | 11 | 4340 | BC connected | All not connected | Correct | Wrong | Wrong | 0.985 |
| 16 | Standard | YES | 108 | 109 | 105 | 0 | 372 | 125 | 99 | 148 | 11 | 4340 | ABC connected | BC connected | Wrong | Correct | Correct | 0.627 |
| 17 | Standard | YES | 108 | 104 | 100 | 4 | 372 | 105 | 99 | 123 | 0 | 5425 | B connected | All not connected | Correct | Wrong | Correct | 0.999 |
| 18 | Standard | YES | 108 | 104 | 100 | 4 | 372 | 105 | 99 | 123 | 0 | 5425 | AB connected | All not connected | Wrong | Wrong | Correct | 0.954 |
| 19 | Standard | YES | 108 | 104 | 100 | 4 | 372 | 105 | 99 | 123 | 0 | 5425 | BC connected | All not connected | Correct | Wrong | Wrong | 0.996 |
| 20 | Standard | YES | 108 | 104 | 100 | 4 | 372 | 105 | 99 | 123 | 0 | 5425 | ABC connected | All not connected | Wrong | Wrong | Wrong | 0.996 |
| 21 | Brighter | NO | 72 | 109 | 105 | 8 | 351 | 105 | 125 | 98 | 0 | 4340 | B connected | B connected | Correct | Correct | Correct | 0.998 |
| 22 | Brighter | NO | 72 | 109 | 105 | 8 | 351 | 105 | 125 | 98 | 0 | 4340 | AB connected | B connected | Wrong | Correct | Correct | 0.885 |
| 23 | Brighter | NO | 72 | 109 | 105 | 8 | 351 | 105 | 125 | 98 | 0 | 4340 | BC connected | B connected | Correct | Correct | Wrong | 0.998 |
| 24 | Brighter | NO | 72 | 109 | 105 | 8 | 351 | 105 | 125 | 98 | 0 | 4340 | ABC connected | ABC connected | Correct | Correct | Correct | 0.955 |
| 25 | Brighter | NO | 72 | 114 | 100 | 0 | 372 | 105 | 147 | 123 | 21 | 6500 | B connected | B connected | Correct | Correct | Correct | 0.724 |
| 26 | Brighter | NO | 72 | 114 | 100 | 0 | 372 | 105 | 147 | 123 | 21 | 6500 | AB connected | B connected | Wrong | Correct | Correct | 0.996 |
| 27 | Brighter | NO | 72 | 114 | 100 | 0 | 372 | 105 | 147 | 123 | 21 | 6500 | BC connected | BC connected | Correct | Correct | Correct | 0.996 |
| 28 | Brighter | No | 73 | 114 | 100 | 0 | 372 | 105 | 147 | 123 | 21 | 6500 | ABC connected | B connected | Wrong | Correct | Wrong | 0.995 |
| 29 | Brighter | NO | 72 | 104 | 95 | 8 | 394 | 125 | 147 | 98 | 11 | 6500 | B connected | B connected | Correct | Correct | Correct | 0.995 |
| 30 | Brighter | NO | 72 | 104 | 95 | 8 | 394 | 125 | 147 | 98 | 11 | 6500 | AB connected | B connected | Wrong | Correct | Correct | 0.995 |
| 31 | Brighter | NO | 72 | 104 | 95 | 8 | 394 | 125 | 147 | 98 | 11 | 6500 | BC connected | ABC connected | Wrong | Correct | Correct | 0.873 |
| 32 | Brighter | NO | 72 | 104 | 95 | 8 | 394 | 125 | 147 | 98 | 11 | 6500 | ABC connected | ABC connected | Correct | Correct | Correct | 0.904 |
| 33 | Brighter | NO | 72 | 114 | 105 | 0 | 394 | 145 | 99 | 148 | 21 | 4340 | B connected | B connected | Correct | Correct | Correct | 0.974 |
| 34 | Brighter | NO | 72 | 114 | 105 | 0 | 394 | 145 | 99 | 148 | 21 | 4340 | AB connected | B connected | Wrong | Correct | Correct | 0.995 |
| 35 | Brighter | NO | 72 | 114 | 105 | 0 | 394 | 145 | 99 | 148 | 21 | 4340 | BC connected | BC connected | Correct | Correct | Correct | 0.852 |
| 36 | Brighter | NO | 72 | 114 | 105 | 0 | 394 | 145 | 99 | 148 | 21 | 4340 | ABC connected | B connected | Wrong | Correct | Wrong | 0.975 |
| 37 | Brighter | NO | 72 | 109 | 100 | 4 | 351 | 125 | 99 | 148 | 0 | 5425 | B connected | B connected | Correct | Correct | Correct | 0.975 |
| 38 | Brighter | NO | 72 | 109 | 100 | 4 | 351 | 125 | 99 | 148 | 0 | 5425 | AB connected | B connected | Wrong | Correct | Correct | 0.999 |
| 39 | Brighter | NO | 72 | 109 | 100 | 4 | 351 | 125 | 99 | 148 | 0 | 5425 | BC connected | BC connected | Correct | Correct | Correct | 0.998 |
| 40 | Brighter | NO | 72 | 109 | 100 | 4 | 351 | 125 | 99 | 148 | 0 | 5425 | ABC connected | B connected | Wrong | Correct | Wrong | 0.819 |
| 41 | Standard | NO | 90 | 114 | 105 | 8 | 372 | 125 | 147 | 123 | 0 | 4340 | B connected | BC connected | Correct | Correct | Wrong | 0.983 |
| 42 | Standard | NO | 90 | 114 | 105 | 8 | 372 | 125 | 147 | 123 | 0 | 4340 | AB connected | B connected | Wrong | Correct | Correct | 0.997 |
| 43 | Standard | NO | 90 | 114 | 105 | 8 | 372 | 125 | 147 | 123 | 0 | 4340 | BC connected | BC connected | Correct | Correct | Correct | 0.999 |
| 44 | Standard | NO | 90 | 114 | 105 | 8 | 372 | 125 | 147 | 123 | 0 | 4340 | ABC connected | B connected | Wrong | Correct | Wrong | 0.985 |
| 45 | Standard | NO | 90 | 109 | 100 | 4 | 394 | 125 | 125 | 98 | 21 | 4340 | B connected | B connected | Correct | Correct | Correct | 0.999 |
| 46 | Standard | NO | 90 | 109 | 100 | 4 | 394 | 125 | 125 | 98 | 21 | 4340 | AB connected | B connected | Wrong | Correct | Correct | 0.999 |
| 47 | Standard | NO | 90 | 109 | 100 | 4 | 394 | 125 | 125 | 98 | 21 | 4340 | BC connected | BC connected | Correct | Correct | Correct | 0.999 |
| 48 | Standard | No | 90 | 109 | 100 | 4 | 394 | 125 | 125 | 98 | 21 | 4340 | ABC connected | ABC connected | Correct | Correct | Correct | 0.999 |
| 49 | Standard | NO | 90 | 104 | 105 | 0 | 394 | 105 | 99 | 98 | 0 | 6500 | B connected | B connected | Correct | Correct | Correct | 0.999 |
| 50 | Standard | NO | 90 | 104 | 105 | 0 | 394 | 105 | 99 | 98 | 0 | 6500 | AB connected | B connected | Wrong | Correct | Correct | 0.999 |
| 51 | Standard | NO | 90 | 104 | 105 | 0 | 394 | 105 | 99 | 98 | 0 | 6500 | BC connected | B connected | Correct | Correct | Wrong | 0.995 |
| 52 | Standard | NO | 90 | 104 | 105 | 0 | 394 | 105 | 99 | 98 | 0 | 6500 | ABC connected | B connected | Wrong | Correct | Wrong | 0.947 |
| 53 | Standard | NO | 90 | 104 | 95 | 8 | 372 | 145 | 99 | 148 | 11 | 5425 | B connected | B connected | Correct | Correct | Correct | 0.999 |
| 54 | Standard | NO | 90 | 104 | 95 | 8 | 372 | 145 | 99 | 148 | 11 | 5425 | AB connected | B connected | Wrong | Correct | Correct | 0.999 |
| 55 | Standard | NO | 90 | 104 | 95 | 8 | 372 | 145 | 99 | 148 | 11 | 5425 | BC connected | B connected | Correct | Correct | Wrong | 0.991 |
| 56 | Standard | NO | 90 | 104 | 95 | 8 | 372 | 145 | 99 | 148 | 11 | 5425 | ABC connected | B connected | Wrong | Correct | Wrong | 0.961 |
| 57 | Standard | NO | 90 | 114 | 100 | 0 | 351 | 145 | 125 | 148 | 0 | 5425 | B connected | BC connected | Correct | Correct | Wrong | 0.982 |
| 58 | Standard | NO | 90 | 114 | 100 | 0 | 351 | 145 | 125 | 148 | 0 | 5425 | AB connected | B connected | Wrong | Correct | Correct | 0.920 |
| 59 | Standard | NO | 90 | 114 | 100 | 0 | 351 | 145 | 125 | 148 | 0 | 5425 | BC connected | BC connected | Correct | Correct | Correct | 0.999 |
| 60 | Standard | NO | 90 | 114 | 100 | 0 | 351 | 145 | 125 | 148 | 0 | 5425 | ABC connected | B connected | Wrong | Correct | Wrong | 0.558 |
| 61 | Brighter | NO | 108 | 114 | 95 | 8 | 351 | 105 | 99 | 123 | 21 | 5425 | B connected | B connected | Correct | Correct | Correct | 0.727 |
| 62 | Brighter | NO | 108 | 114 | 95 | 8 | 351 | 105 | 99 | 123 | 21 | 5425 | AB connected | B connected | Wrong | Correct | Correct | 0.980 |
| 63 | Brighter | NO | 108 | 114 | 95 | 8 | 351 | 105 | 99 | 123 | 21 | 5425 | BC connected | BC connected | Correct | Correct | Correct | 0.655 |
| 64 | Brighter | NO | 108 | 114 | 95 | 8 | 351 | 105 | 99 | 123 | 21 | 5425 | ABC connected | B connected | Wrong | Correct | Wrong | 0.981 |
| 65 | Brighter | NO | 108 | 104 | 105 | 4 | 394 | 145 | 125 | 123 | 11 | 5425 | B connected | B connected | Correct | Correct | Correct | 0.621 |
| 66 | Brighter | NO | 108 | 104 | 105 | 4 | 394 | 145 | 125 | 123 | 11 | 5425 | AB connected | B connected | Wrong | Correct | Correct | 0.984 |
| 67 | Brighter | NO | 108 | 104 | 105 | 4 | 394 | 145 | 125 | 123 | 11 | 5425 | BC connected | ABC connected | Wrong | Correct | Correct | 0.956 |
| 68 | Brighter | NO | 108 | 104 | 105 | 4 | 394 | 145 | 125 | 123 | 11 | 5425 | ABC connected | ABC connected | Correct | Correct | Correct | 0.999 |
| 69 | Brighter | NO | 108 | 109 | 95 | 0 | 372 | 145 | 147 | 98 | 0 | 6500 | B connected | BC connected | Correct | Correct | Wrong | 0.983 |
| 70 | Brighter | NO | 108 | 109 | 95 | 0 | 372 | 145 | 147 | 98 | 0 | 6500 | AB connected | B connected | Wrong | Correct | Correct | 0.651 |
| 71 | Brighter | NO | 108 | 109 | 95 | 0 | 372 | 145 | 147 | 98 | 0 | 6500 | BC connected | ABC connected | Wrong | Correct | Correct | 0.556 |
| 72 | Brighter | NO | 108 | 109 | 95 | 0 | 372 | 145 | 147 | 98 | 0 | 6500 | ABC connected | ABC connected | Correct | Correct | Correct | 0.999 |
| 73 | Brighter | NO | 108 | 114 | 100 | 4 | 394 | 105 | 99 | 98 | 11 | 4340 | B connected | BC connected | Correct | Correct | Wrong | 0.949 |
| 74 | Brighter | NO | 108 | 114 | 100 | 4 | 394 | 105 | 99 | 98 | 11 | 4340 | AB connected | B connected | Correct | Correct | Correct | 0.999 |
| 75 | Brighter | NO | 108 | 114 | 100 | 4 | 394 | 105 | 99 | 98 | 11 | 4340 | BC connected | BC connected | Correct | Correct | Correct | 0.999 |
| 76 | Brighter | NO | 108 | 114 | 100 | 4 | 394 | 105 | 99 | 98 | 11 | 4340 | ABC connected | ABC connected | Correct | Correct | Correct | 0.988 |
| 77 | Brighter | NO | 108 | 104 | 100 | 8 | 372 | 125 | 125 | 148 | 21 | 6500 | B connected | B connected | Correct | Correct | Correct | 0.998 |
| 78 | Brighter | NO | 108 | 104 | 100 | 8 | 372 | 125 | 125 | 148 | 21 | 6500 | AB connected | B connected | Wrong | Correct | Correct | 0.981 |

| Run | Illumination | Disturbances | Camera Horizontal angle relative to object | Camera height | Distance | Focus | Zoom | Brightness | Sharpness | Contrast | Saturation | White balance | True combination | Predicted label | Clamp A | Clamp B | Clamp C | P-value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 79 | Brighter | NO | 108 | 104 | 100 | 8 | 372 | 125 | 125 | 148 | 21 | 6500 | BC connected | B connected | Correct | Correct | Wrong | 0.991 |
| 80 | Brighter | NO | 108 | 104 | 100 | 8 | 372 | 125 | 125 | 148 | 21 | 6500 | ABC connected | ABC connected | Correct | Correct | Correct | 0.962 |
| 81 | Brighter | YES | 90 | 109 | 95 | 4 | 372 | 105 | 147 | 148 | 21 | 5425 | B connected | B connected | Correct | Correct | Correct | 0.985 |
| 82 | Brighter | YES | 90 | 109 | 95 | 4 | 372 | 105 | 147 | 148 | 21 | 5425 | AB connected | B connected | Wrong | Correct | Correct | 0.999 |
| 83 | Brighter | YES | 90 | 109 | 95 | 4 | 372 | 105 | 147 | 148 | 21 | 5425 | BC connected | BC connected | Correct | Correct | Correct | 0.531 |
| 84 | Brighter | YES | 90 | 109 | 95 | 4 | 372 | 105 | 147 | 148 | 21 | 5425 | ABC connected | B connected | Wrong | Correct | Wrong | 0.999 |
| 85 | Brighter | YES | 90 | 104 | 95 | 0 | 351 | 125 | 125 | 123 | 0 | 4340 | B connected | BC connected | Correct | Correct | Wrong | 0.989 |
| 86 | Brighter | YES | 90 | 104 | 95 | 0 | 351 | 125 | 125 | 123 | 0 | 4340 | AB connected | BC connected | Wrong | Correct | Wrong | 0.697 |
| 87 | Brighter | YES | 90 | 104 | 95 | 0 | 351 | 125 | 125 | 123 | 0 | 4340 | BC connected | BC connected | Correct | Correct | Correct | 0.976 |
| 88 | Brighter | YES | 90 | 104 | 95 | 0 | 351 | 125 | 125 | 123 | 0 | 4340 | ABC connected | ABC connected | Correct | Correct | Correct | 0.955 |
| 89 | Brighter | YES | 90 | 109 | 105 | 8 | 351 | 145 | 99 | 123 | 21 | 6500 | B connected | No objects | N/V | N/V | N/V | N/V |
| 90 | Brighter | YES | 90 | 109 | 105 | 8 | 351 | 145 | 99 | 123 | 21 | 6500 | AB connected | B connected | Wrong | Correct | Correct | 0.604 |
| 91 | Brighter | YES | 90 | 109 | 105 | 8 | 351 | 145 | 99 | 123 | 21 | 6500 | BC connected | BC connected | Correct | Correct | Correct | 0.975 |
| 92 | Brighter | YES | 90 | 109 | 105 | 8 | 351 | 145 | 99 | 123 | 21 | 6500 | ABC connected | ABC connected | Correct | Correct | Correct | 0.998 |
| 93 | Brighter | YES | 90 | 114 | 100 | 0 | 372 | 145 | 125 | 98 | 11 | 6500 | B connected | BC connected | Correct | Correct | Wrong | 0.984 |
| 94 | Brighter | YES | 90 | 114 | 100 | 0 | 372 | 145 | 125 | 98 | 11 | 6500 | AB connected | B connected | Wrong | Correct | Correct | 0.753 |
| 95 | Brighter | YES | 90 | 114 | 100 | 0 | 372 | 145 | 125 | 98 | 11 | 6500 | BC connected | BC connected | Correct | Correct | Correct | 0.972 |
| 96 | Brighter | YES | 90 | 114 | 100 | 0 | 372 | 145 | 125 | 98 | 11 | 6500 | ABC connected | B connected | Wrong | Correct | Wrong | 0..542 |
| 97 | Brighter | YES | 90 | 114 | 105 | 4 | 394 | 125 | 147 | 148 | 0 | 5425 | B connected | B connected | Correct | Correct | Correct | 0.559 |
| 98 | Brighter | YES | 90 | 114 | 105 | 4 | 394 | 125 | 147 | 148 | 0 | 5425 | AB connected | B connected | Wrong | Correct | Correct | 0.991 |
| 99 | Brighter | YES | 90 | 114 | 105 | 4 | 394 | 125 | 147 | 148 | 0 | 5425 | BC connected | BC connected | Correct | Correct | Correct | 0.728 |
| 100 | Brighter | YES | 90 | 114 | 105 | 4 | 394 | 125 | 147 | 148 | 0 | 5425 | ABC connected | AC connected | Correct | Wrong | Correct | 0.842 |
| 101 | Brighter | YES | 90 | 104 | 100 | 0 | 394 | 145 | 147 | 148 | 21 | 4340 | B connected | No objects | N/V | N/V | N/V | N/V |
| 102 | Brighter | YES | 90 | 104 | 100 | 0 | 394 | 145 | 147 | 148 | 21 | 4340 | AB connected | No objects | N/V | N/V | N/V | N/V |
| 103 | Brighter | YES | 90 | 104 | 100 | 0 | 394 | 145 | 147 | 148 | 21 | 4340 | BC connected | BC connected | Correct | Correct | Correct | 0.981 |
| 104 | Brighter | YES | 90 | 104 | 100 | 0 | 394 | 145 | 147 | 148 | 21 | 4340 | ABC connected | ABC connected | Correct | Correct | Correct | 0.781 |
| 105 | Brighter | YES | 90 | 109 | 105 | 4 | 351 | 105 | 147 | 148 | 11 | 6500 | B connected | BC connected | Correct | Correct | Wrong | 0.915 |
| 106 | Brighter | YES | 90 | 109 | 105 | 4 | 351 | 105 | 147 | 148 | 11 | 6500 | AB connected | B connected | Wrong | Correct | Correct | 0.987 |
| 107 | Brighter | YES | 90 | 109 | 105 | 4 | 351 | 105 | 147 | 148 | 11 | 6500 | BC connected | BC connected | Correct | Correct | Correct | 0.987 |
| 108 | Brighter | YES | 90 | 109 | 105 | 4 | 351 | 105 | 147 | 148 | 11 | 6500 | ABC connected | B connected | Wrong | Correct | Wrong | 0.697 |
| 109 | Brighter | YES | 90 | 109 | 100 | 8 | 394 | 125 | 99 | 123 | 11 | 6500 | B connected | B connected | Correct | Correct | Correct | 0.999 |
| 110 | Brighter | YES | 90 | 109 | 100 | 8 | 394 | 125 | 99 | 123 | 11 | 6500 | AB connected | B connected | Wrong | Correct | Correct | 0.999 |
| 111 | Brighter | YES | 90 | 109 | 100 | 8 | 394 | 125 | 99 | 123 | 11 | 6500 | BC connected | BC connected | Correct | Correct | Correct | 0.969 |
| 112 | Brighter | YES | 90 | 109 | 100 | 8 | 394 | 125 | 99 | 123 | 11 | 6500 | ABC connected | ABC connected | Correct | Correct | Correct | 0.996 |
| 113 | Brighter | YES | 90 | 104 | 95 | 4 | 372 | 145 | 99 | 98 | 0 | 4340 | B connected | BC connected | Correct | Correct | Wrong | 0.755 |
| 114 | Brighter | YES | 90 | 104 | 95 | 4 | 372 | 145 | 99 | 98 | 0 | 4340 | AB connected | No objects | N/V | N/V | N/V | N/V |
| 115 | Brighter | YES | 90 | 104 | 95 | 4 | 372 | 145 | 99 | 98 | 0 | 4340 | BC connected | BC connected | Correct | Correct | Correct | 0.873 |
| 116 | Brighter | YES | 90 | 104 | 95 | 4 | 372 | 145 | 99 | 98 | 0 | 4340 | ABC connected | ABC connected | Correct | Correct | Correct | 0.992 |
| 117 | Brighter | YES | 90 | 114 | 105 | 8 | 372 | 125 | 125 | 98 | 11 | 5425 | B connected | No objects | N/V | N/V | N/V | N/V |
| 118 | Brighter | YES | 90 | 114 | 105 | 8 | 372 | 125 | 125 | 98 | 11 | 5425 | AB connected | A connected | Correct | Wrong | Wrong | 0.810 |
| 119 | Brighter | YES | 90 | 114 | 105 | 8 | 372 | 125 | 125 | 98 | 11 | 5425 | BC connected | ABC connected | Wrong | Correct | Correct | 0.569 |
| 120 | Brighter | YES | 90 | 114 | 105 | 8 | 372 | 125 | 125 | 98 | 11 | 5425 | ABC connected | ABC connected | Correct | Correct | Correct | 0.998 |
| 121 | Standard | YES | 72 | 109 | 95 | 0 | 394 | 145 | 125 | 123 | 11 | 5425 | B connected | B connected | Correct | Correct | Correct | 0.998 |
| 122 | Standard | YES | 72 | 109 | 95 | 0 | 394 | 145 | 125 | 123 | 11 | 5425 | AB connected | B connected | Wrong | Correct | Correct | 0.999 |
| 123 | Standard | YES | 72 | 109 | 95 | 0 | 394 | 105 | 125 | 123 | 11 | 5425 | BC connected | B connected | Correct | Correct | Wrong | 0.942 |
| 124 | Standard | YES | 72 | 109 | 95 | 0 | 394 | 105 | 125 | 123 | 11 | 5425 | ABC connected | B connected | Wrong | Correct | Wrong | 0.984 |
| 125 | Standard | YES | 72 | 114 | 95 | 4 | 351 | 125 | 99 | 98 | 21 | 6500 | B connected | B connected | Correct | Correct | Correct | 0.568 |
| 126 | Standard | YES | 72 | 114 | 95 | 4 | 351 | 125 | 99 | 98 | 21 | 6500 | AB connected | A connected | Correct | Wrong | Wrong | 0.546 |
| 127 | Standard | YES | 72 | 114 | 95 | 4 | 351 | 125 | 99 | 98 | 21 | 6500 | BC connected | B connected | Correct | Correct | Wrong | 0.772 |
| 128 | Standard | YES | 73 | 114 | 95 | 4 | 351 | 125 | 99 | 98 | 21 | 6500 | ABC connected | ABC connected | Correct | Correct | Correct | 0.595 |
| 129 | Standard | YES | 72 | 109 | 100 | 8 | 394 | 145 | 147 | 98 | 0 | 5425 | B connected | B connected | Correct | Correct | Correct | 0.925 |
| 130 | Standard | YES | 72 | 109 | 100 | 8 | 394 | 145 | 147 | 98 | 0 | 5425 | AB connected | B connected | Wrong | Correct | Wrong | 0.985 |
| 131 | Standard | YES | 72 | 109 | 100 | 8 | 394 | 145 | 147 | 98 | 0 | 5425 | BC connected | BC connected | Correct | Correct | Correct | 0.999 |
| 132 | Standard | YES | 72 | 109 | 100 | 8 | 394 | 145 | 147 | 98 | 0 | 5425 | ABC connected | ABC connected | Correct | Correct | Correct | 0.764 |
| 133 | Standard | YES | 72 | 104 | 105 | 4 | 372 | 145 | 125 | 123 | 21 | 6500 | B connected | B connected | Correct | Correct | Correct | 0.964 |
| 134 | Standard | YES | 72 | 104 | 105 | 4 | 372 | 145 | 125 | 123 | 21 | 6500 | AB connected | ABC connected | Correct | Correct | Wrong | 0.620 |
| 135 | Standard | YES | 72 | 104 | 105 | 4 | 372 | 145 | 125 | 123 | 21 | 6500 | BC connected | ABC connected | Wrong | Correct | Wrong | 0.693 |
| 136 | Standard | YES | 72 | 104 | 105 | 4 | 372 | 145 | 125 | 123 | 21 | 6500 | ABC connected | AC connected | Correct | Wrong | Correct | 0.899 |
| 137 | Standard | YES | 72 | 104 | 100 | 8 | 351 | 105 | 147 | 148 | 11 | 4340 | B connected | B connected | Correct | Correct | Correct | 0.514 |
| 138 | Standard | YES | 72 | 104 | 100 | 8 | 351 | 105 | 147 | 148 | 11 | 4340 | AB connected | All not connected | Wrong | Wrong | Correct | 0.508 |
| 139 | Standard | YES | 72 | 104 | 100 | 8 | 351 | 105 | 147 | 148 | 11 | 4340 | BC connected | All not connected | Correct | Wrong | Wrong | 0.969 |
| 140 | Standard | YES | 72 | 104 | 100 | 8 | 351 | 105 | 147 | 148 | 11 | 4340 | ABC connected | All not connected | Wrong | Wrong | Wrong | 0.730 |

**Appendix B Table 1.** *The Design of Experiment for the Robustness test*

# Appendix C

The recommended setup established during the Exploratory Testing. This setup was further used to create the AI vision model to perform the robust test.

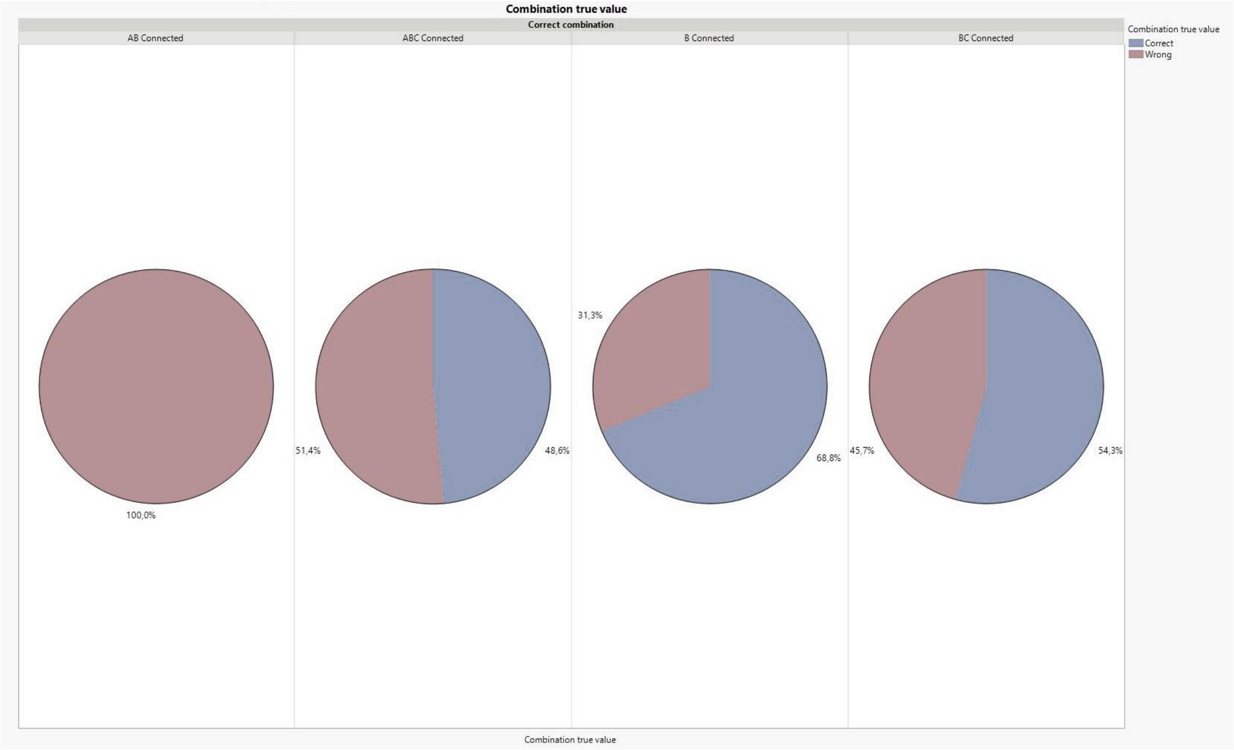
| Area | Factor | Setup |
|---|---|---|
| Environmental setup | Training location | At the intended workstation |
| | Line setup | Stationary line |
| | Illumination | Standard |
| | Background disturbances | Standardised |
| Software settings for machine learning | Label classification | Single Label classification |
| | Storage | Cloud Storage |
| | Training accuracy | High accuracy |
| | Number of images per label | 900 |
| | Time for ML | 40 *Node hours* |
| | Number of labels | 8 |
| Camera setup | Camera height | 109 cm |
| | Camera angle towards the object | 90° straight forward |
| | Distance between camera and object | 100 cm |
| | Zoom | 372 |
| | Focus | 0 |
| | Brightness | 125 |
| | Sharpness | 125 |
| | Contrast | 123 |
| | Saturation | 0 |
| | White balance | 5425 |
| Object to detect | Type of object | Binary (Clamp) |
| | Number of Objects to detect | 3 |
| | Position of object | To the Left<br>Centralised in the middle<br>To the right |
| | Colour of object | Chrome (different from background) |

**Appendix C Table 1.** *The Setup for the Robustness test*

# Appendix D

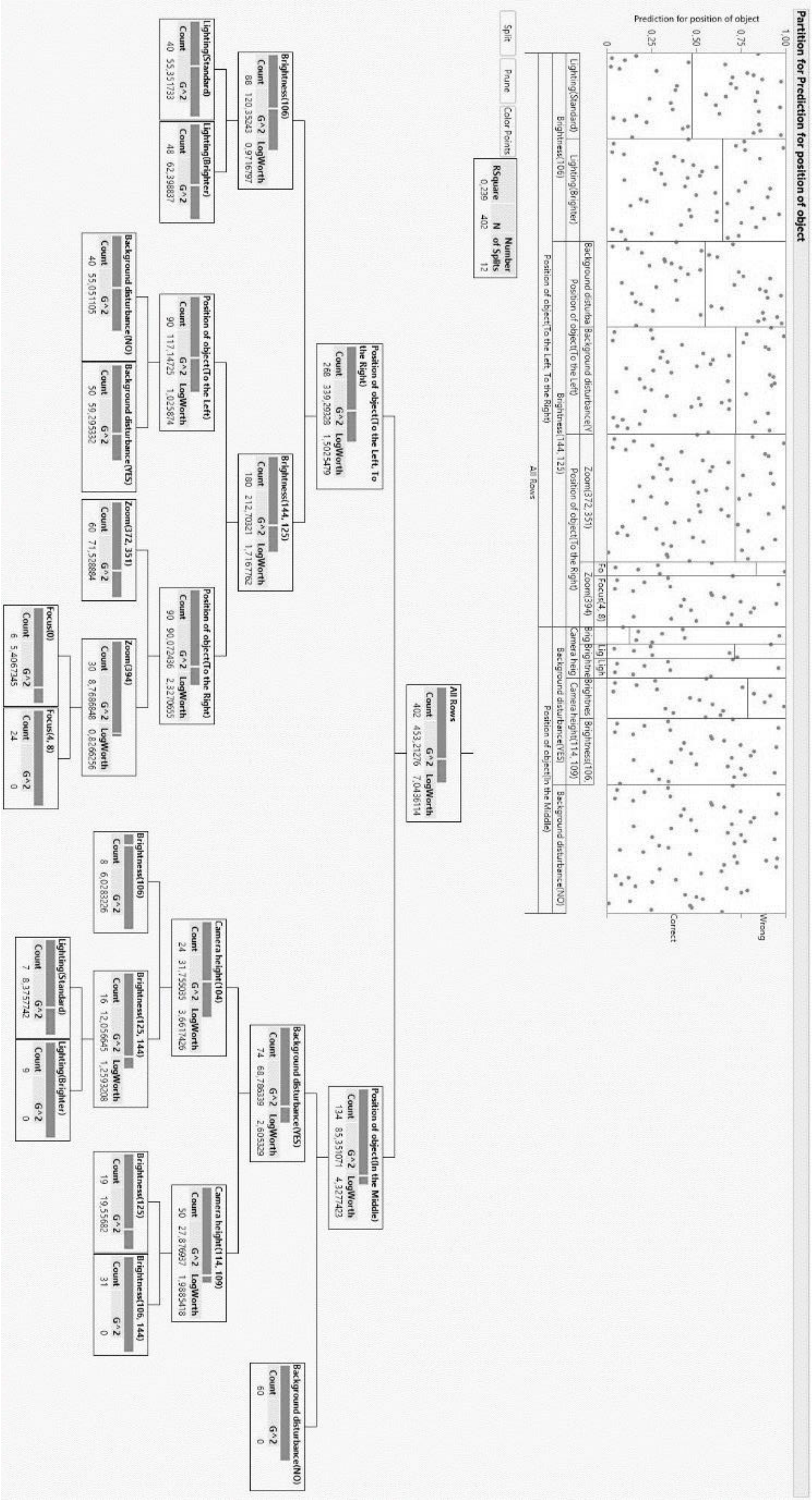
The following appendix contains figures and short descriptions of the different correlations and findings made during the robustness test.

**Appendix D Figure 1** shows that none of the four combinations had more than 70% correct. The four combinations were, AB-connected, ABC-connected, B-connected, and BC-connected. The combination of true value equals the AI vision system ability to predict correct or wrong.



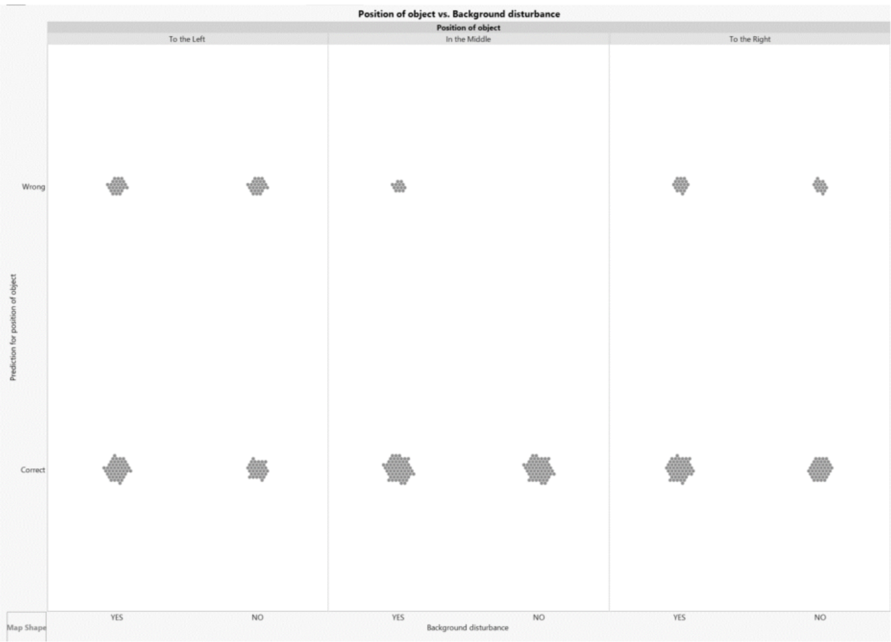
**Appendix D Figure 1.** *Combination true value VS combination of clamps*

**Appendix D Figure 2** below shows that positioning of object should be in the middle and that the additional background disturbances was the reason for the errors that occurred.



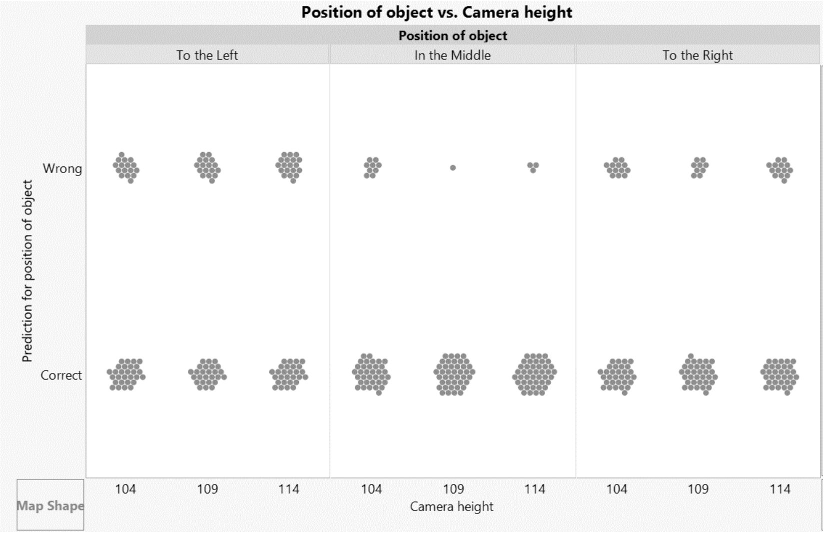
**Appendix D Figure 2.** *Analysis of the impacted factors with regard to position of object*

**Appendix D Figure 3** below shows that background disturbances impacted the clamp in the middle very much while the outer clamps were not affected that much. This was because there were a lot of errors that occurred for the outer clamps despite there were no additional background disturbances.



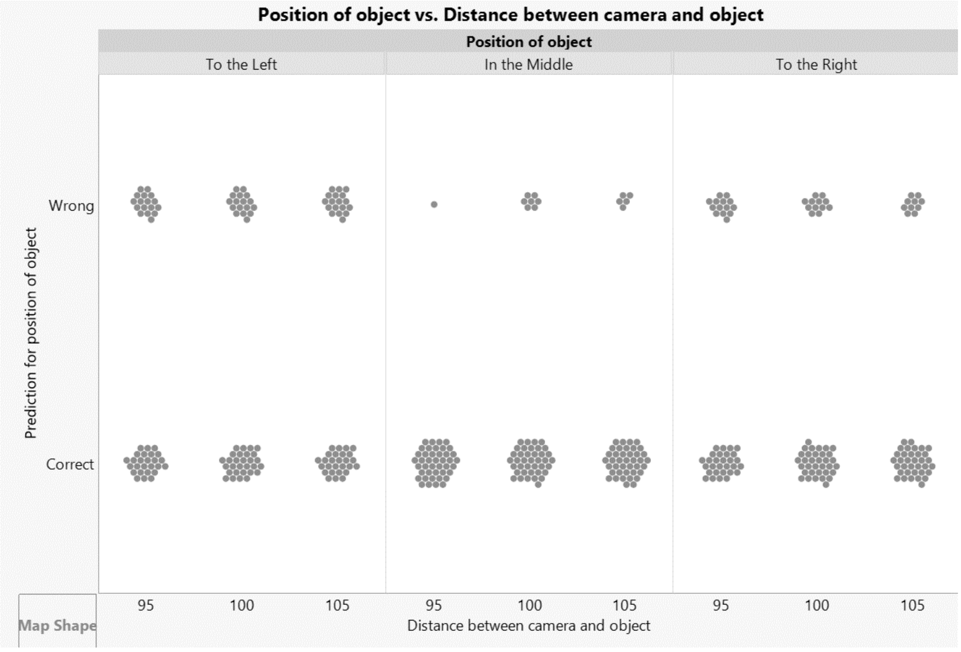
**Appendix D Figure 3.** *Position of object VS Background disturbances*

**Appendix D Figure 4** below shows that the camera height impacted the object positioned in the middle the least. However, the lower height was considered as the least appropriate. Having the clamp positioned in the middle at the same height as during the training provided the system with the best performance. It could also be noted that the camera height was not really optimised for the outer two clamps since the error rate were quite high during the trained height.



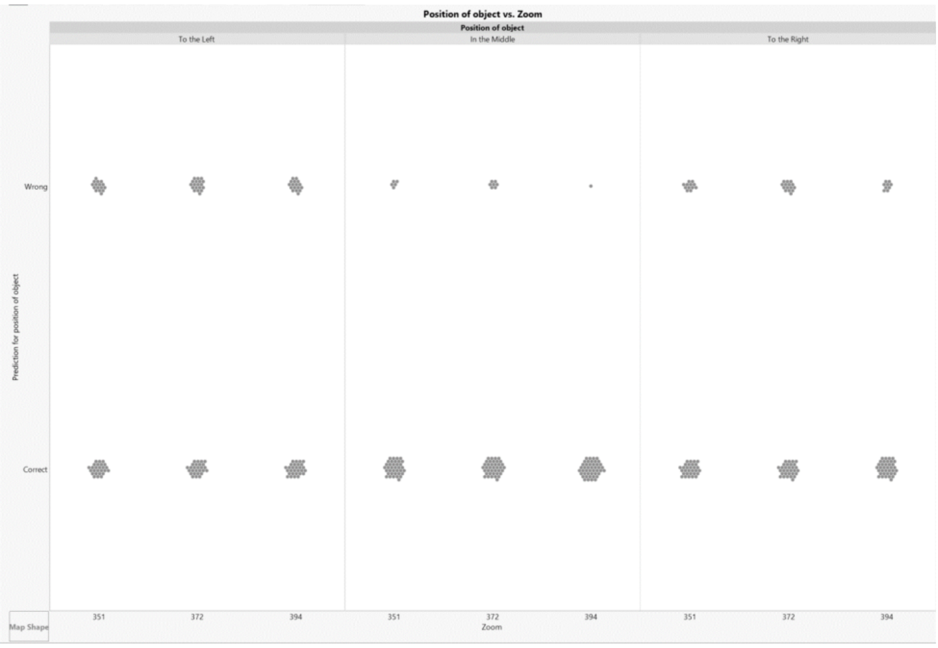
**Appendix D Figure 4.** *Position of object VS Camera height*

**Appendix D Figure 5** below shows that the distance between camera and object for the object positioned in the middle had the least errors occurred. The distance did not significantly affect the error rate at the outer two clamps.



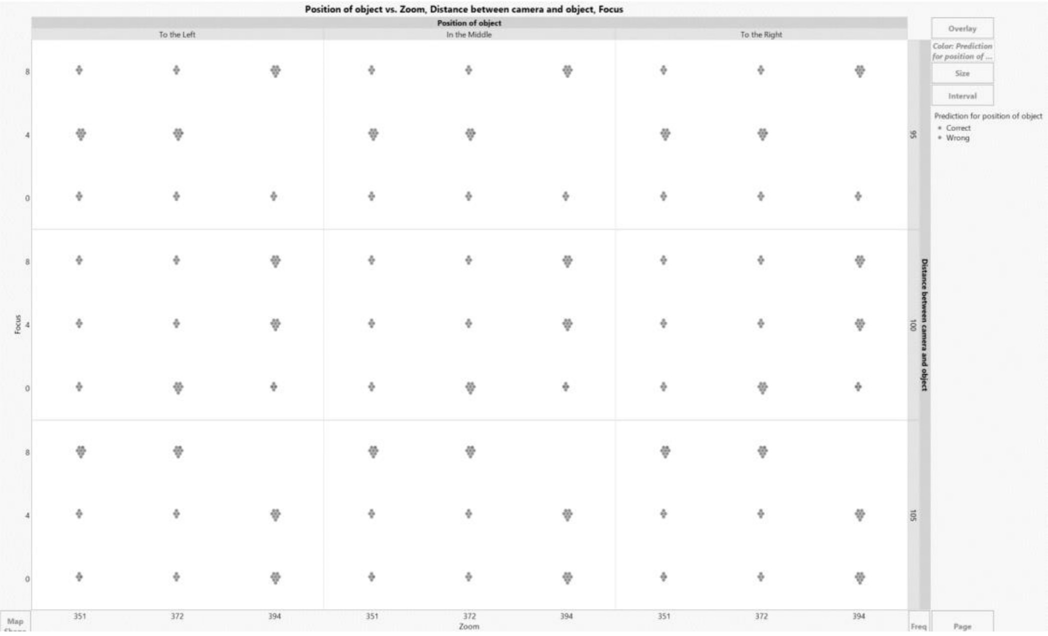
**Appendix D Figure 5.** *Position of object VS Distance between camera and object*

**Appendix D Figure 6** below shows that the middle clamp reacted the least to the changes of the Zoom.



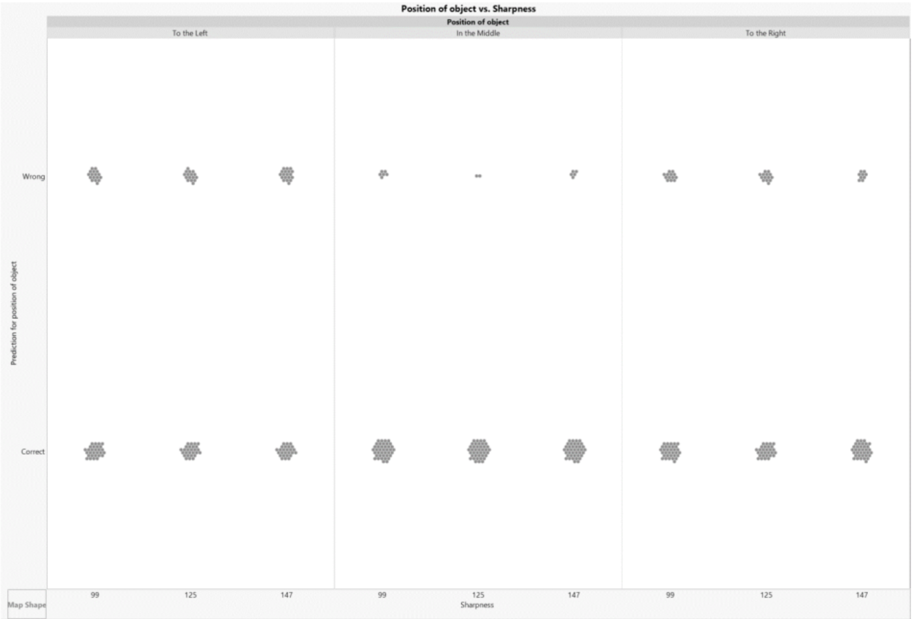
**Appendix D Figure 6.** *Position of objects VS Zoom*

**Appendix D Figure 7** blew shows the different combinations of Zoom, Focus and Distance between camera and object.



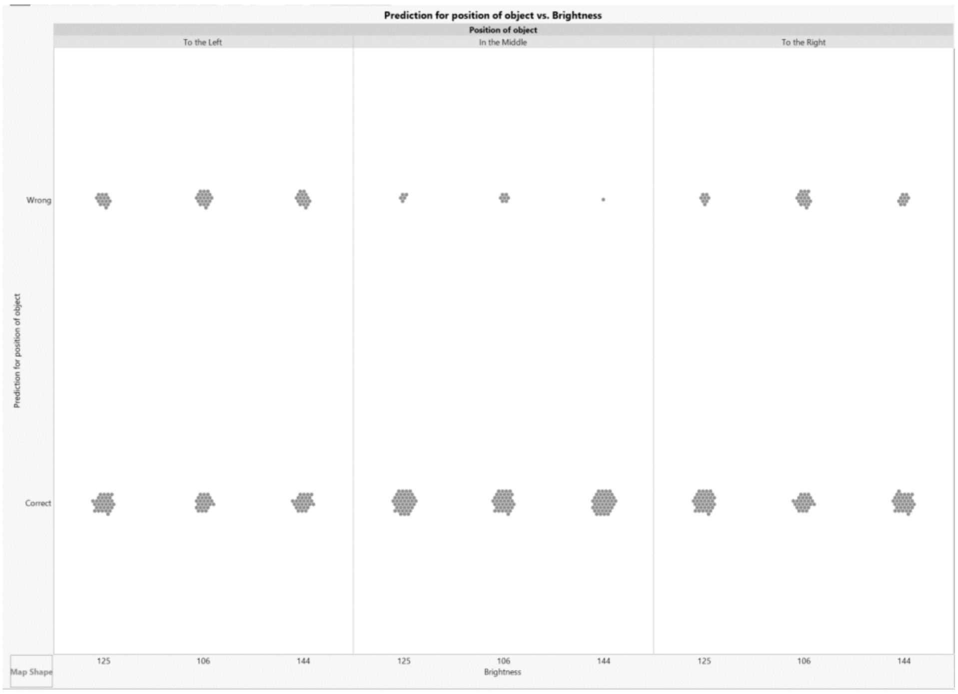
**Appendix D Figure 7.** *Combination: Focus, Zoom & Distance between camera and object*

**Appendix D Figure 8** below shows that sharpness during the same setting as trained (125) had the best performance.



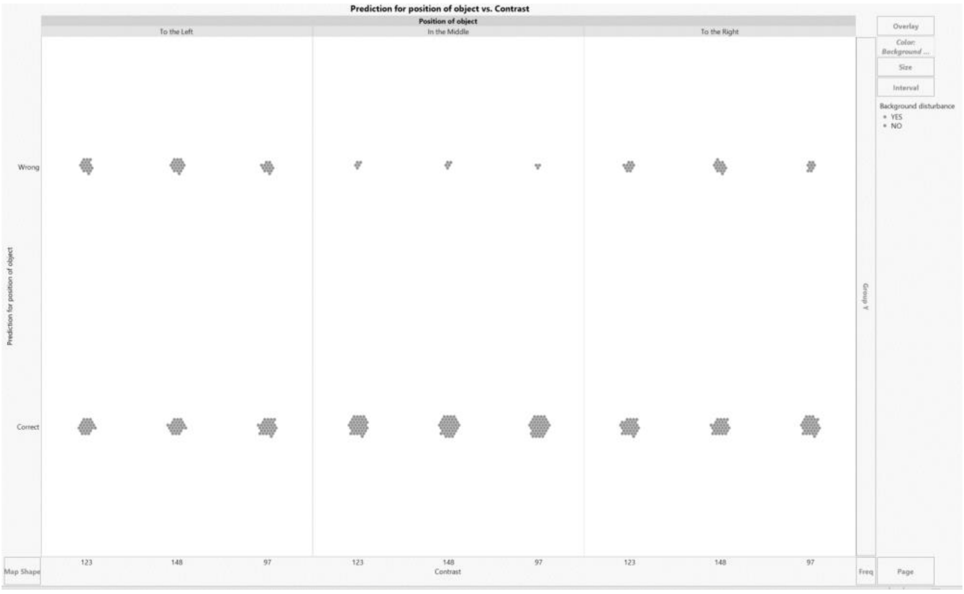
**Appendix D Figure 8.** *Position of object VS Sharpness*

**Appendix D Figure 9** below shows that the highest setting for Brightness within the process window had the best performance.



**Appendix D Figure 9.** *Position of object VS Brightness*

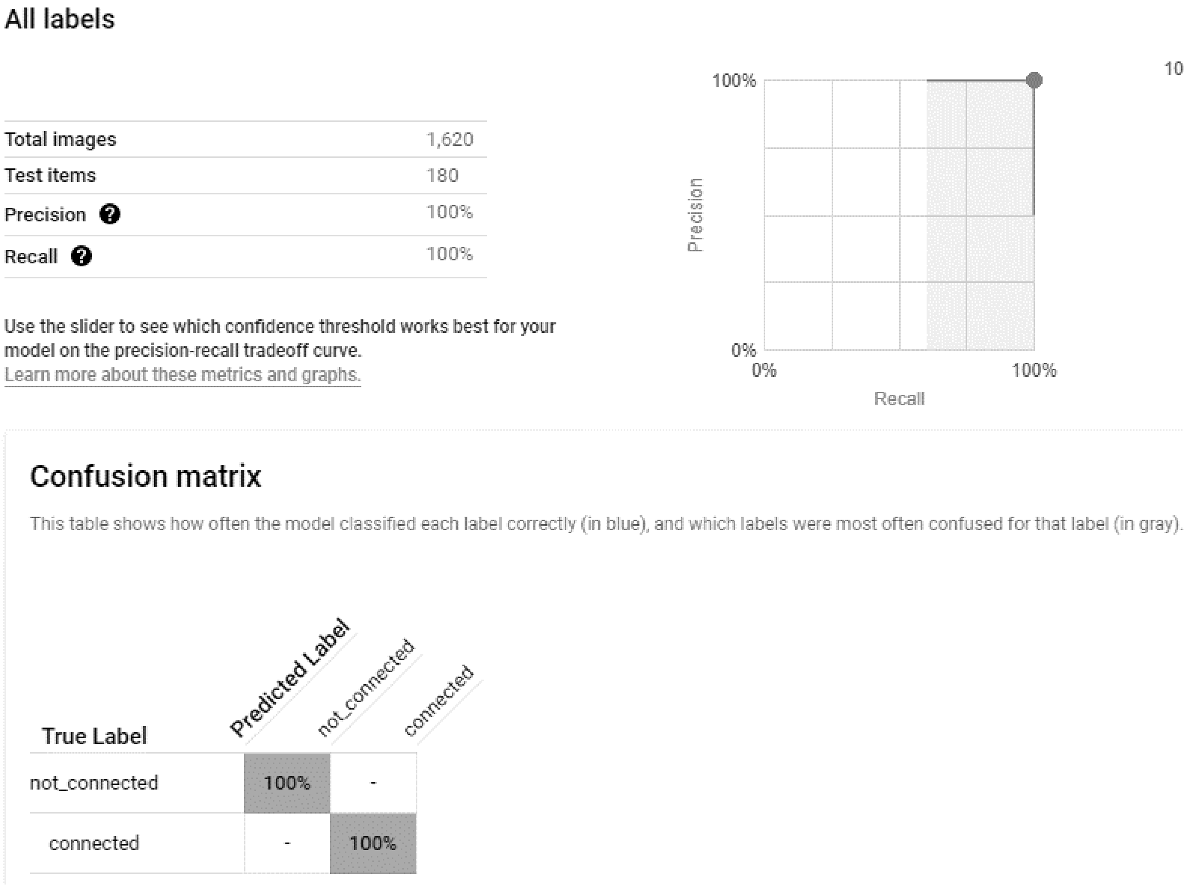
**Appendix D Figure 10** below shows that the contrast did not vary much within the process window.



**Appendix D Figure 10.** *Position of object VS Contrast*

# Appendix E

The following appendix contains figures and short descriptions of the different correlations and findings made during the final test.



## All labels

| | |
|---|---|
| Total images | 1,620 |
| Test items | 180 |
| Precision | 100% |
| Recall | 100% |

Use the slider to see which confidence threshold works best for your model on the precision-recall tradeoff curve.
Learn more about these metrics and graphs.

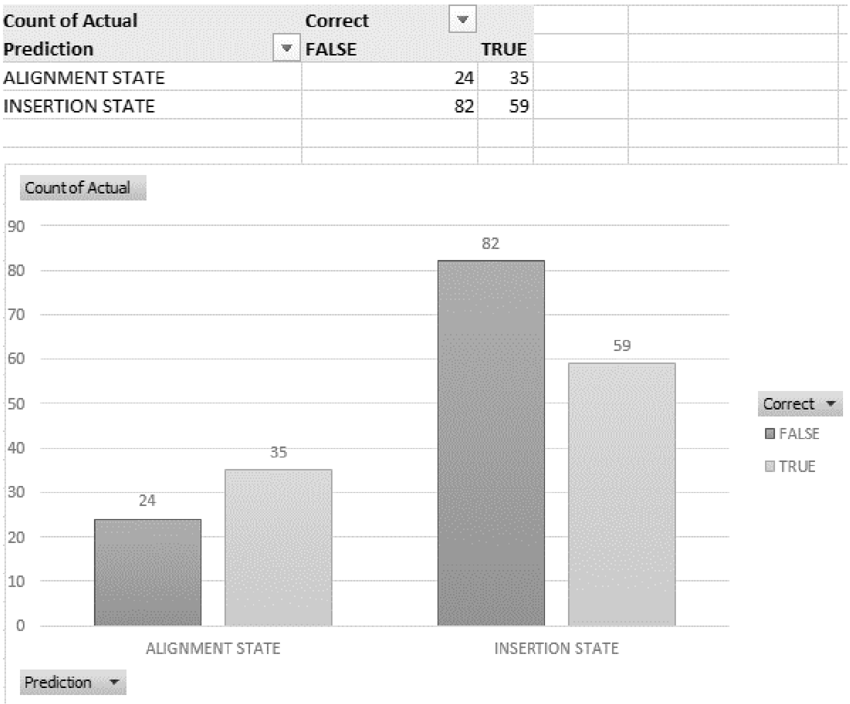
## Confusion matrix

This table shows how often the model classified each label correctly (in blue), and which labels were most often confused for that label (in gray).

Predicted Label

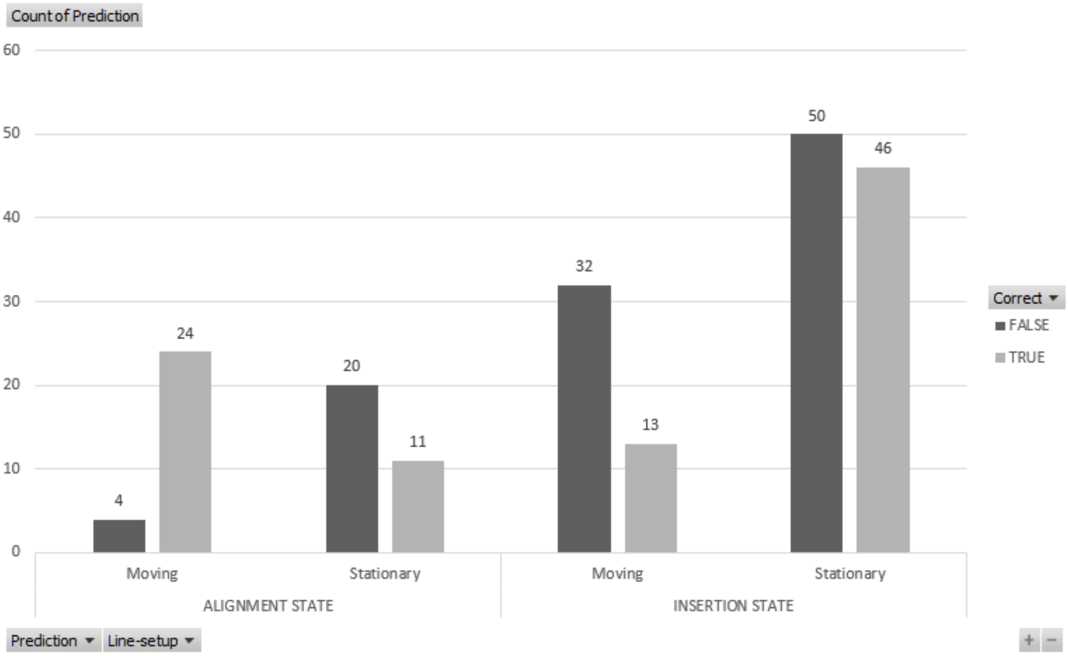
| True Label | not_connected | connected |
|---|---|---|
| not_connected | 100% | - |
| connected | - | 100% |

**Appendix E Figure 1.** *Evaluation of the model for the final test*

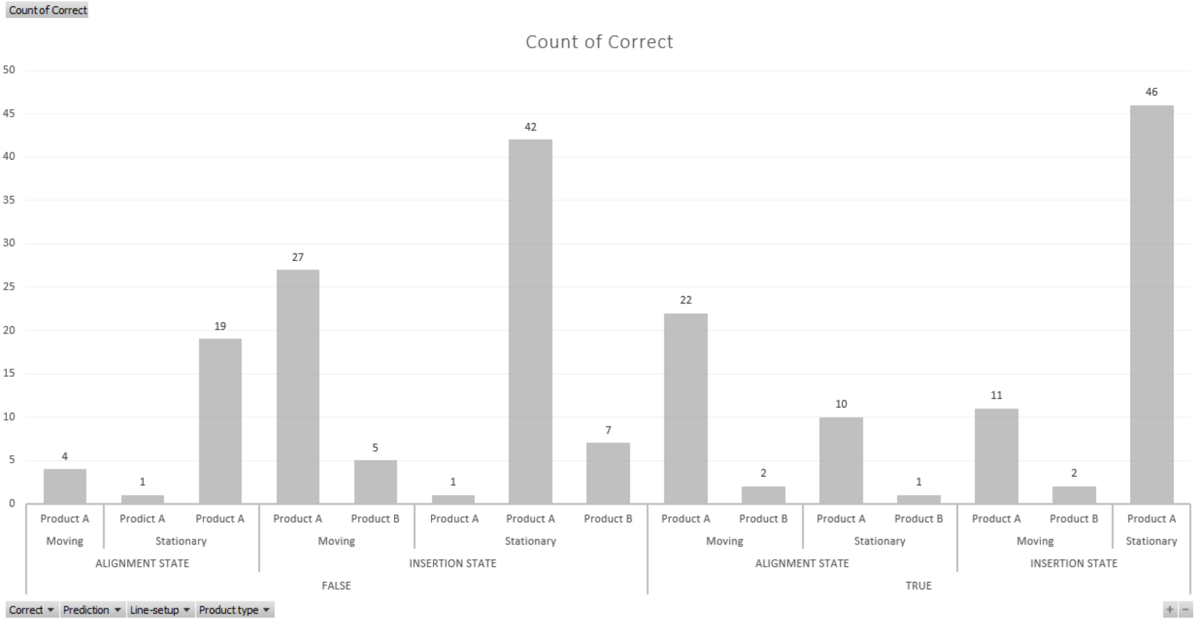


| Count of Actual | Correct | |
|---|---|---|
| Prediction | FALSE | TRUE |
| ALIGNMENT STATE | 24 | 35 |
| INSERTION STATE | 82 | 59 |

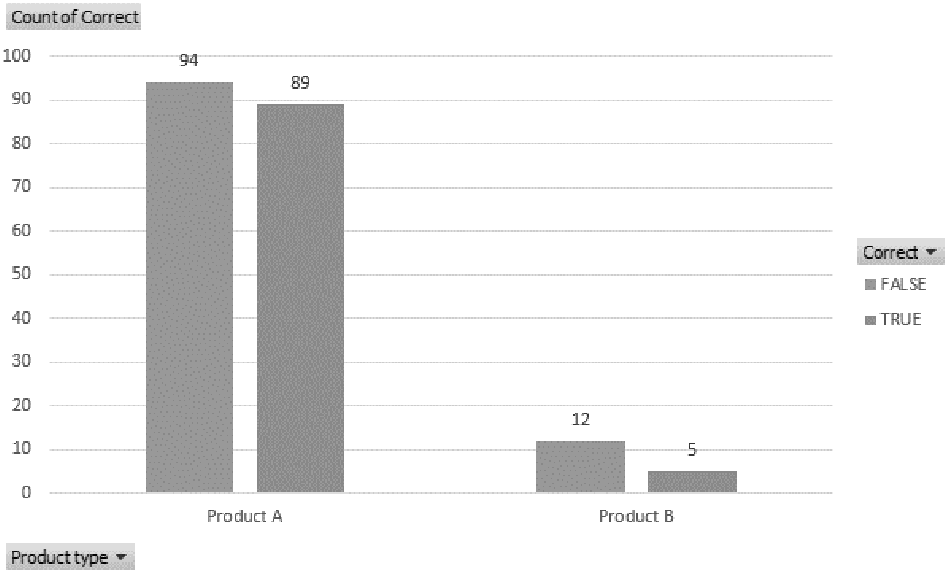
**Appendix E Figure 2.** *The number of predictions for the two states of the clamp*



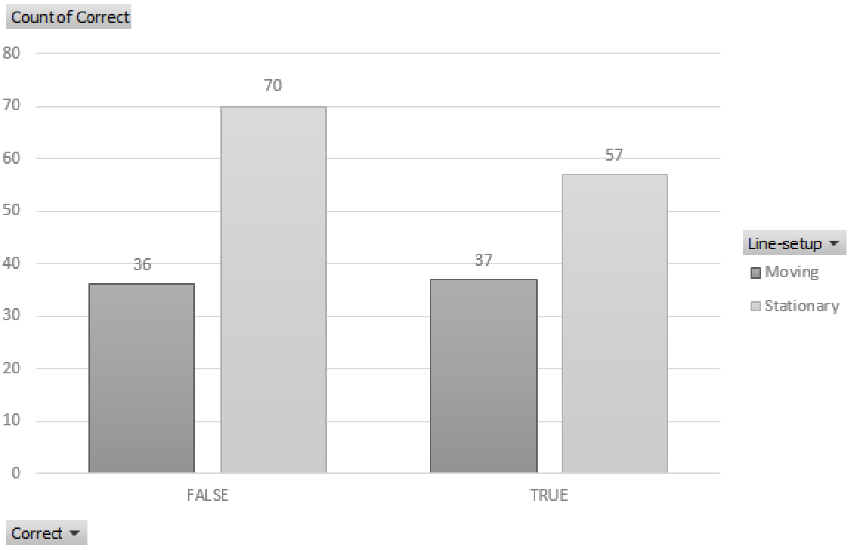
**Appendix E Figure 3.** *Result of final test with regard to Line setup*



**Appendix E Figure 4.** *A cross analysis of the result and factors studied*



**Appendix E Figure 5.** The result with regard to the product variants



**Appendix E Figure 6.** *The result with regard to line-setup*

**Appendix E Table 1.** *The correct and wrong predictions of the final test*

| NO | Prediction | Actual | Line-setup | Product type | Correct |
|---|---|---|---|---|---|
| 1 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 2 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 3 | ALIGNED | ALIGNED | Moving | Product B | TRUE |
| 4 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 5 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 6 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 7 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 8 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 9 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 10 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 11 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 12 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 13 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 14 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 15 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 16 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 17 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 18 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 19 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 20 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 21 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 22 | NOT ALIGNED | ALIGNED | Stationary | Product B | FALSE |
| 23 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 24 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 25 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 26 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 27 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 28 | NOT ALIGNED | ALIGNED | Moving | Product B | FALSE |
| 29 | NOT ALIGNED | ALIGNED | Stationary | Product B | FALSE |
| 30 | NOT ALIGNED | ALIGNED | Stationary | Product B | FALSE |
| 31 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 32 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 33 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 34 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 35 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 36 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 37 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 38 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 39 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 40 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 41 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |

| NO | Prediction | Actual | Line-setup | Product type | Correct |
|---|---|---|---|---|---|
| 42 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 43 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 44 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 45 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 46 | ALIGNED | ALIGNED | Moving | Product B | TRUE |
| 47 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 48 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 49 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 50 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 51 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 52 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 53 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 54 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 55 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 56 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 57 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 58 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 59 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 60 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 61 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 62 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 63 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 64 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 65 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 66 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 67 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 68 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 69 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 70 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 71 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 72 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 73 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 74 | ALIGNED | ALIGNED | Stationary | Product A | TRUE |
| 75 | NOT ALIGNED | ALIGNED | Moving | Product B | FALSE |
| 76 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 77 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 78 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 79 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 80 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 81 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 82 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 83 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 84 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |

| NO | Prediction | Actual | Line-setup | Product type | Correct |
|---|---|---|---|---|---|
| 85 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 86 | NOT ALIGNED | ALIGNED | Moving | Product B | FALSE |
| 87 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 88 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 89 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 90 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 91 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 92 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 93 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 94 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 95 | NOT ALIGNED | ALIGNED | Moving | Product B | FALSE |
| 96 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 97 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 98 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 99 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 100 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 101 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 102 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 103 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 104 | ALIGNED | NOT ALIGNED | Moving | Product A | FALSE |
| 105 | NOT ALIGNED | NOT ALIGNED | Moving | Product B | TRUE |
| 106 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 107 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 108 | NOT ALIGNED | NOT ALIGNED | Moving | Product B | TRUE |
| 109 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 110 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 111 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 112 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 113 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 114 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 115 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 116 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 117 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 118 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 119 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 120 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 121 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 122 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 123 | ALIGNED | NOT ALIGNED | Moving | Product A | FALSE |
| 124 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 125 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 126 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 127 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |

| NO | Prediction | Actual | Line-setup | Product type | Correct |
|---|---|---|---|---|---|
| 128 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 129 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 130 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 131 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 132 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 133 | ALIGNED | NOT ALIGNED | Moving | Product A | FALSE |
| 134 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 135 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 136 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 137 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 138 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 139 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 140 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 141 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 142 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 143 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 144 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 145 | ALIGNED | NOT ALIGNED | Moving | Product A | FALSE |
| 146 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 147 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 148 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 149 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 150 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 151 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 152 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 153 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 154 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 155 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 156 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 157 | ALIGNED | NOT ALIGNED | Stationary | Product A | FALSE |
| 158 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 159 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 160 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 161 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 162 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 163 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 164 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 165 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 166 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 167 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 168 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 169 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 170 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |

| NO | Prediction | Actual | Line-setup | Product type | Correct |
|---|---|---|---|---|---|
| 171 | NOT ALIGNED | NOT ALIGNED | Stationary | Product A | TRUE |
| 172 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 173 | NOT ALIGNED | NOT ALIGNED | Moving | Product A | TRUE |
| 174 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 175 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 176 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 177 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 178 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 179 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 180 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 181 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 182 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 183 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 184 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 185 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 186 | ALIGNED | ALIGNED | Moving | Product A | TRUE |
| 187 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 188 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 189 | NOT ALIGNED | ALIGNED | Stationary | Product A | FALSE |
| 190 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 191 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 192 | NOT ALIGNED | ALIGNED | Moving | Product B | FALSE |
| 193 | NOT ALIGNED | ALIGNED | Stationary | Product B | FALSE |
| 194 | ALIGNED | ALIGNED | Stationary | Product B | TRUE |
| 195 | NOT ALIGNED | ALIGNED | Stationary | Product B | FALSE |
| 196 | NOT ALIGNED | ALIGNED | Stationary | Product B | FALSE |
| 197 | NOT ALIGNED | ALIGNED | Stationary | Product B | FALSE |
| 198 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 199 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |
| 200 | NOT ALIGNED | ALIGNED | Moving | Product A | FALSE |

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