MACHINE LEARNING FOR DECISION-MAKING IN THE REMANUFACTURING OF WORN-OUT GEARS AND BEARINGS

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ABSTRACT

Mechanical industries use rotating mechanical equipment in their day to day operations. The equipment suffers from wear and tear, and is usually discarded as scrap. But is there a way to recover some of this equipment and reuse it? This paper uses machine learning to capture and analyse the wearing damage of bearings and gears to determine whether they can be redeemed. Finite element analysis is conducted on worn-out spur gears and pillow bearings in order to facilitate feature extraction in image processing algorithms. This converts the actual gears, bearings, and seals into CAD files. The decision-making system is designed, and it uses these CAD files to decide on the optimum manufacturing process to restore redeemable components. The mechanical components of the system are designed using SOLIDWORKS. MATLAB, Proteus software, and the Arduino micro-controller are used for the system application design and simulation. The results from tests conducted on a worn-out gear and bearing show that the gear is 4% non-redeemable, while the bearing is 60.2% non-redeemable. The decision taken by the system is to redeem the gear and to discard the bearing.

OPSOMMING

Roterende meganiese toerusting word daagliks in die meganiese bedryf gebruik. Hierdie toerusting ondergaan slytasie en word gereeld as skroot afgeskryf. Hierdie artikel gebruik masjienleer om slytasie van laers en ratte vas te vang en te ontleed om te bepaal of hulle herbruik kan word. Eindige element analise is toegepas op geslyte reguittand ratte en kussinglaers om kenmerk ontrekking vir beeldverwerkingsalgoritmes te fasiliteer. Hierdie proses vang die werklike ratte, laers en seëls as CAD tekeninge vas en besluit dan op die optimale prosesse om herbruikbare onderdele te herstel. Die meganiese onderdele van die stelsel is ontwerp deur van SOLID WORKS, MATLAB en Proteus sagteware gebruik te maak. ʼn Arduino mikro-beheerder is gebruik vir die stelsel toepassingsontwerp. Die resultate van toetse op ʼn geslyte rat en laer toon dat die rat 4% nie herbruikbaar is nie en die laer 60.2% nie herbruikbaar is nie. Die rat word dus herwerk en die laer word geskrap.

1 INTRODUCTION

Technological advances in the manufacturing industry warrant reduced energy use and the conservation of materials. Unlike in the past, when scrapyards were filled with equipment parts that were considered unredeemable, recent years have seen a rise in the reuse and recycling of material. The advent of tribology, remanufacturing, and demanufacturing has shown the potential for recovering worn-out equipment. There is a challenge when companies keep on piling up worn-out machine equipment, such as faulty gears and defective bearings and seals at dumpsites. This is particularly evident with power plants and mining and railway companies. This research is based, therefore, on using machine learning to capture and analyse the wearing damage of bearings and gears to determine whether they can be redeemed. Power Plant ABC and XYZ Railway Company, whose dumpsites had piles of faulty gears and defective pillow bearings and seals are used as case studies. Figure 1 below shows Power Plant ABC's scrap metal dumpsite.

Figure 1: Power Plant ABC's scrap metal dumpsite

The motivation behind this research is that these companies have been ordering and/or manufacturing new bearings to replace the worn-out ones. High procurement costs and unwanted dumpsites are the order of the day. These scrapyards often remain like that for many years, and they contribute to environmental degradation. Scrapyards are usually unhygienic and pose a health risk to workers [1]. They also cause heavy-metal pollution on the surface and are potentially sources of metal ions leaking into ground water [1-2]. Thus, in this research, machine learning assists in the decision-making process for the remanufacturing of worn-out gears and bearings. Once bearings and gears lose their efficiency from wear and tear, they are removed, and a finite element analysis (FEA) of the spur gear and pillow bearing is done to facilitate feature extraction in image processing algorithms. 3D measurement, imaging, and scanning technology are then used to convert the real gears, bearings, and seals into the CAD system. The machine learning restoration system then determines the redeemability of a worn-out bearing or gear by extracting its features through image processing, and is used to decide on the optimum restoration of the equipment.

Defective parts that are regarded as scrap can be regenerated or restored to their functional state through remanufacturing, depending on the extent to which they have been damaged. This study compares the additive manufacturing (AM) technologies of selective laser melting (SLM) and wire arc additive manufacturing (WAAM). The major challenge of remanufacturing is the uncertainty associated with the variations in the quality of final products. AM counters this uncertainty by offering flexible production, adding material layer by layer [4]. In addition, AM has the ability to manufacture end-use products sustainably with virtually no raw material loss, as opposed to the conventional subtractive methods [5]. Most mechanical industries and workshops are now moving from the traditional subtractive manufacturing and moving towards AM, which saves energy and reduces material wastage. AM has also been shown to have potential for remanufacturing, in which it is used to recover worn-out machine components and to restore end-of-life components to an almost new condition [6]. This saves raw materials, energy and production time [4]. However, it has some limitations. Huge capital investments, difficulties in storing the flammable powders, product size limits, surface roughness, and low suitability for mass production are some of the barriers hindering its application [7]. Thus, this study compares AM with the traditional methods of manufacture for a given set of parameters, and selects the best.

2 LITERATURE REVIEW

2.1 Remanufacturing, and its benefits

Remanufacturing is a process in which a used or worn-out part can be rebuilt and restored to the specifications of an originally manufactured product [8]. It involves cleaning, disassembly of the components, inspection, and reassembly [9]. As a recycling and recovering process, it enables manufacturers to improve the part's quality without having to replace it with a completely new product [10]. It improves raw material utilisation by repairing parts that would otherwise be discarded as scrap. It uses less energy [11] — that is, 80% less than when a new product or part is to be manufactured. Furthermore, up to 85% of the worn-out material can be restored in the remanufactured part [12]. According to the Remanufacturing Industries Council, the benefits of remanufacturing include high cost savings for companies and low buying prices for customers, reduced landfills, a reduced consumption of raw materials, a reduced lead time, low energy consumption, and reduced CO_2 emissions [13].

Lahroura and Brissauda [4] developed a framework for additive remanufacturing with which the manufacturer can decide about the redeemability of a worn-out product. In the event that the product is redeemable, the framework provides a basis for making a decision about its remanufacturability, based on a comparison between the direct energy deposition and the powder bed fusion processes. It is imperative to note that this framework relies on the knowledge of the manufacturer. Decisions are made on the basis of the input that the manufacturer makes into the system.

It is important to verify whether remanufacturing is the best option in relation to cost savings. Bayındır *et al*. [14] constructed a steady-profit model that focuses on the conditions under which remanufacturing or manufacturing a new product (one-way substitution) could increase profitability. The analysis is about whether a product should be manufactured or remanufactured, and is based on resolving the following issues: the economics of remanufacturing versus the demand stream for the remanufactured products; a comparison of the profitability of manufacturing a new product versus remanufacturing; and how manufacturing a new product might impact the inventory-related profits.

Afrinaldi *et al*. [15] compared the eco-efficiency of a remanufactured diesel engine cylinder block with that of a newly manufactured cylinder block. The study showed that remanufacturing resulted in savings of between 88% and 99% in raw material usage, energy consumption and emissions into the environment, a 90% reduction in global warming potentials (GWP), and a 39% reduction in cost.

2.2 Selected additive manufacturing methods

2.2.1 Selective laser melting (SLM)

Selective laser melting (SLM) melts and fuses metal powder layer by layer with a high-power density laser [16]. It has the ability to melt the metal powder fully and to produce fully dense (almost 100%) near net shapes [17]. It produces a product that has good mechanical properties [18] that are comparable with bulk materials [19]. Thus, it is well-suited to redeeming gears and bearings.

The main challenge with laser-based technologies is residual stresses [20]. These stresses remain inherent in the built part even when it has reached equilibrium with its environment. Every manufacturing process introduces a certain level of residual stress [21]. However, laser-based technologies introduce more, owing to the high thermal gradients that occur in the process [22]. This calls for post-processing stress relief methods to be applied, such as stress-relief heat treatment.

2.2.2 Wire arc additive manufacturing (WAAM)

Wire arc additive manufacturing (WAAM) is an additive manufacturing process that produces parts layer by layer using the gas metal arc welding (GMAW) technology [23]. It uses metal wires instead of powder as an additive, and laser as the energy source, in order to produce full-density components [24]. It is well-suited to building medium to large components. This is due to its high deposition rates (which can reach 10 kg/hr) and unlimited build volume [25]. This caters for bigger gears and bearings. It also has low raw material costs [26] arising from a low buy-to-fly ratio, as the ratio of the starting material to the finished product is almost 1 (one) [27].

Using wire as feed also eliminates the challenges associated with using metal powder, which include controlling particle size and distribution [28]. However, it is also important to note that high temperatures are involved in this process [29], and, just as in the SLM process, post-processing to relieve residual stresses in the product is very important [30].

2.3 Machine learning for decision-making

Machine learning is defined as a set of methods that can automatically detect patterns in data, and then use those patterns to predict future data or to perform other kinds of decision-making under uncertainty [31]. It is a branch of artificial intelligence (AI), which imitates how human beings learn and uses past experience to improve performance and to make efficient and accurate predictions without being explicitly programmed [32]. Machine learning is also used to detect faults, classify defects, and forecast production [33].

Many scholars have investigated the combination of machine learning with image processing for decision-making. This has been widely implemented in the medical field, where it helps to predict illness, make quick and accurate diagnoses, and identify the early stages of sickness, among many other things. Medical imagining analyses such as computerised tomography (CT) scans, ultrasound imaging analysis, magnetic resonance imaging (MRI), and microscopy take full advantage of machine learning [34]. The applicability of machine learning in decision-making also extends to other contexts. Other real-world applications include predictive analytics and intelligent decision-making, in which, for example, machine learning algorithms are used to identify suspects after a crime has been committed, to detect credit card fraud as it takes place, to determine consumer behavior, and to manage inventory to avoid stock running out. Machine learning techniques are also used in cybersecurity, the Industrial Internet of things (IIoT), smart cities, and in image, speech, and pattern recognition [35]. Applying machine learning methods to redeeming worn-out gears and bearings would reduce costs while at the same time contributing to a sustainable environment. The practical application of machine learning in the manufacturing industry is shown in Table 1 below [36] [37] [38] [39] [40] [41] [42]:

Table 1: Practical applications of machine learning

Practical application	Example
Image and pattern recognition	Product classification, defective product recognition in a production line
Production, planning, and control	Automated scheduling, performance prediction, process control
Internet of Things (IoT)	Automation of tasks without human interaction
Maintenance management	Machine condition monitoring, online fault detection of machines, failure mode analysis, predictive maintenance
Quality management	Online quality control, defects detection and classification
Supply chain management	Predicting consumer behaviour, optimising warehousing and logistics
Robotics	Safe human—robot collaboration on the production line
Cybersecurity	Protecting networks from attacks

Machine learning aids remanufacturing, through feature recognition, to determine the redeemability of a product. It provides systems with the ability to learn and improve automatically from experience without being explicitly programmed [43]. In this study, supervised machine learning is used. Image processing identifies the defective gear as a digital image, and analyses it using algorithms. The image is used as the input, and the useful information returns as the output [44]. This enables the system to make a decision about whether or not the bearing or gear is redeemable, and, in the event that it is redeemable, the optimum manufacturing process to be used.

3 RESEARCH METHODOLOGY

'Research methodology' is defined as the general approach a researcher takes in carrying out a research project [45]. It is a way systematically to solve a research problem [46]. It shows the path by which the problem was formulated and how the objectives were defined, and presents the findings [47]. As part of the research methodology of this study, the research methods were primarily based on a case study that was done at Power Plant ABC and XYZ Railway Company. Samples were gathered and analysed to detect the wear patterns on the bearings and gears. This analysis was done with visual inspections of the worn-out work parts and comparing them with new ones from their manufacturers. Measurements were also done with instruments such as Vernier callipers to identify the extent of the wear on the equipment while comparing the measurements with the original equipment specifications.

3.1 Bearings and seal sample collection

New bearing samples were obtained from the retail sellers of various bearings and mechanical seals. Faulty and depleted pillow bearing samples were obtained from Power Plant ABC. The sample size consisted of eight booster fans. Each booster fan had a failed pillow bearing collected from it as a sample. The defective equipment was visually inspected, and parameters such as a wear debris analysis of the lining were taken into consideration to check the extent of the bearings' wear and tear. Figure 2 below shows the bearing failure trend (left) for the discarded pillow block housings (right).

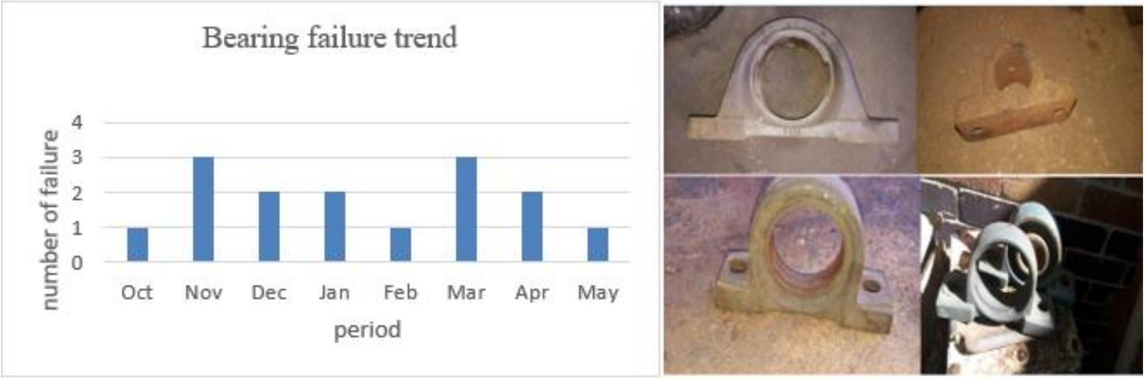

Figure 2: Bearings' failure trend (left) and discarded pillow block housings (right)

The pillow block bearings were found to be more susceptible to wear and tear than other bearings. These bearings and seals were used on booster fans on the boiler. The higher operating speed and poor lubrication resulted in the bearings failing too quickly. From the graph in Figure 2, the average failure per month of these bearings was determined as below:

$$\text{Average monthly failure} = \frac{Total\ failures}{Time\ period}$$

$$= \frac{15\ failures}{8\ months}$$

$$= 1.875\ failures/month$$

As a result of the failures, there has been at least one breakdown per month at Power Plant ABC. Shutting down a section of the plant to replace the worn-out bearings/gears has resulted in a failure to meet monthly production targets.

3.2 Gears sample collection

Gear samples were obtained with the help of the mechanical workshop attendants from Power Plant ABC and XYZ Railway Company. The wear patterns of various worn-out gears were observed, taking measurements to acquire input parameters and specifications for the computer application to be designed in relation to gears. From the case study, the gears that are more susceptible to severe wear and tear are radicon reduction gear boxes (the results from the measurements are shown in Table 2). The sample size of these radicon gear box failures was 12. These gears are used mainly in coal and ash plants. The worm gear in the gearbox is made of chromium steel alloys, and the helical gear ring is made of brass. Figure 3 below shows the breakdown trend as a result, and a collection of discarded gears.

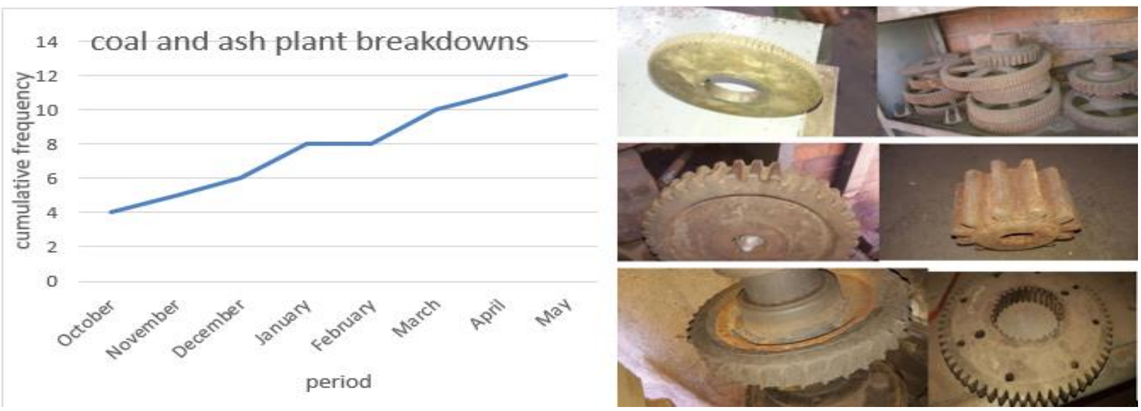

Figure 3: Breakdown trend (left) and collection of discarded gears (right)

Figure 3 also shows the different types of gear that are worn-out and deemed no longer fit for use. The norm is to collect these gears and throw them away in the scrapyard. Over the years, these metal components pile up and take up space. Table 2 below shows the ABC analysis of Power Plant ABC's consumables that have been replaced over a period of a year.

Table 2: ABC analysis of plant consumables that need to be replaced

Plant consumable	Annual volume	Annual volume %	Class	
Booster fan pillow block bearings	24	33.3%	A	83.2%
Reduction gears (worm)	14	19.4%	A	
Conveyor belt rollers	10	13.9%	A	
Stocker motor gears	6	8.3%	A	
Raw water pumps bearings	6	8.3%	A	
CWP bearings	3	4.2%	B	12.6%
Boiler feed pump bearings	2	2.8%	B	
Fluid coupling bearings	2	2.8%	B	
BU pump bearings	2	2.8%	B	
White metal turbine bearings	1	1.4%	C	4.2%
Centrifugal governor gears	1	1.4%	C	
Turbine barring gears	1	1.4%	C	

The pillow block bearings, reduction gears, conveyor belt rollers, stocker motor gears, and raw water pumps bearings fall under class A of the annual volume. This results in these depleted materials being piled up in the scrapyard and being replaced with newly procured items; thus, the system will mainly be focused on gears and pillow bearings.

3.3 Preparation OF THE EQUIPMENT BEFORE ANALYSIS

The defective part — that is, the bearing, gear, or seal — has to be prepared before it is scanned to check the extent of the damage through cleaning. The deep cleaning of the work elements is essential, since the metal will be oxidised; and also, there will be accumulation of grit and oil-based elements such as grease on the metal surface. Figure 4 below shows the general cleaning steps in the remanufacturing process.

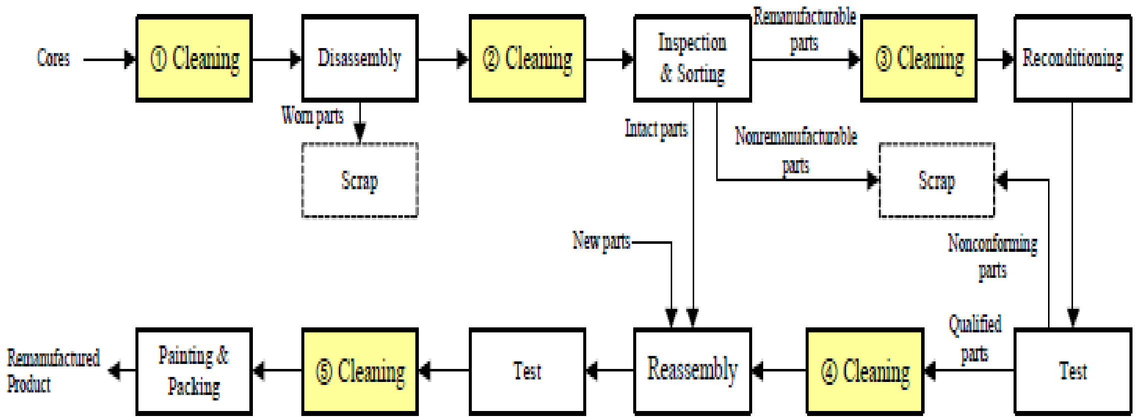

Figure 4: Cleaning in the remanufacturing process [48]

The 'core' in the diagram is a worn-out part. Degreasing and cleaning are necessary processes for materials before working on the machine elements. The quality of the surface cleanliness of the worn-out part determines the analysis that will be done on the surface to determine whether or not it is redeemable, and the reconditioning, reassembly, and painting of the remanufactured product [48]. Chemical cleaning is preferred because, unlike mechanical cleaning, there is no need to dismantle and reassemble the metal equipment. This minimises the equipment's susceptibility to damage.

4 SYSTEM DESIGN

An analysis of the gears and bearings is essential in order to formulate the system requirements, feature extraction, and object detection algorithms. Analysing these deformations allows decision-making about the manufacturing method to use. A probabilistic approach to extracting the geometrical shape deformation makes decisions about whether or not the part in redeemable. A model has been made and examined using SOLIDWORKS software, which provides results equivalent to a physical experiment.

4.1 Mechanical domain

The automated inspection system consists of the control box, which protects the camera and pneumatic components from exposure to dust and unwanted debris during the operation of the system. A proximity sensor senses the component to be inspected by the system, and so is mounted together with the camera. The pneumatic components are mounted inside the control box to facilitate the sorting mechanism, which uses a piston and cylinder.

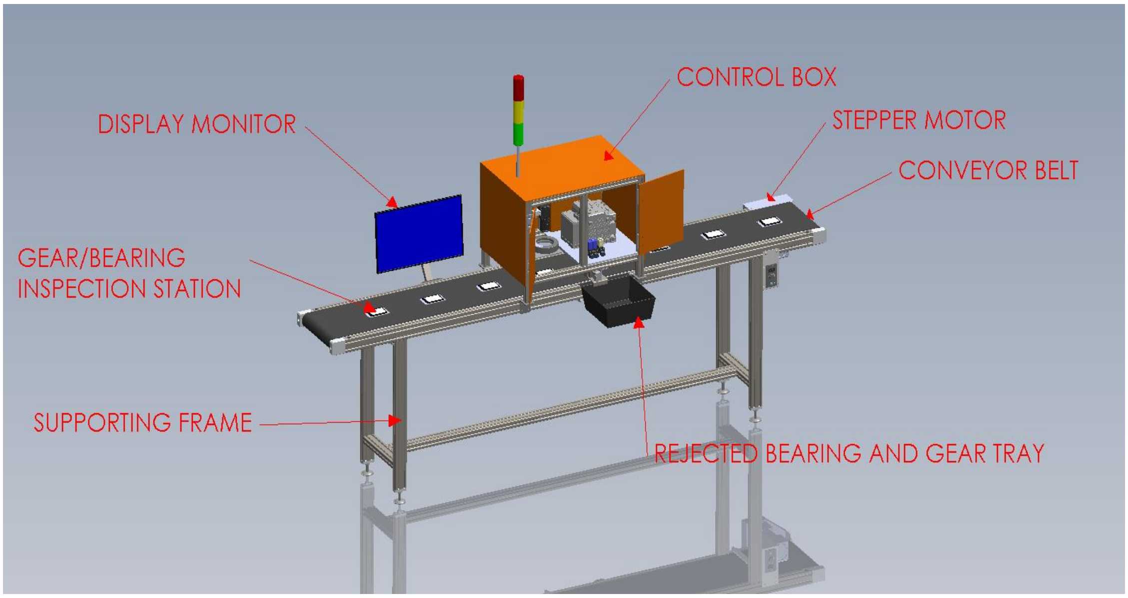

Figure 5: 3D model of the system

The components for the system have the following functions:

- *Gear/bearing inspection station:* this is where the operator places the gear or bearing to be inspected.
- *Conveyor belt:* this carries the gear or bearing for inspection.
- *Display platform:* this displays the results, is mounted together with the system, and is adjustable.
- *Control box:* this protects the camera and pneumatic components from exposure to dust and unwanted debris during the operation of the system.
- *Stepper motor:* this is attached to the frame chassis of the conveyor bed for coupling with the belt.
- *Rejected bearing and gear tray:* this is where the non-redeemable gear or bearing is collected and discarded.
- *Supporting frame:* this holds the mechanical components.

Figure 6 below shows the overall system dimensions, which are all in millimeters.

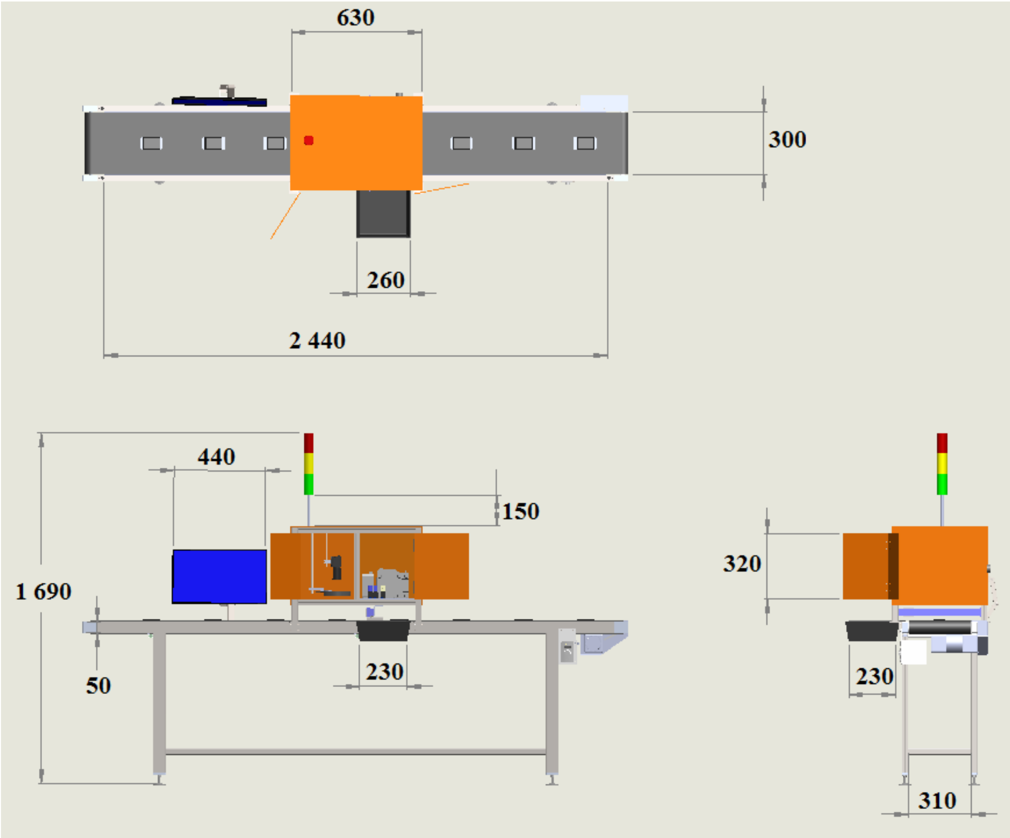

Figure 6: Overall system dimensions

4.2 The control box

The diagram below shows the component arrangement inside the control box housing. The doors are able to swing, since hinges are attached to the housing frame.

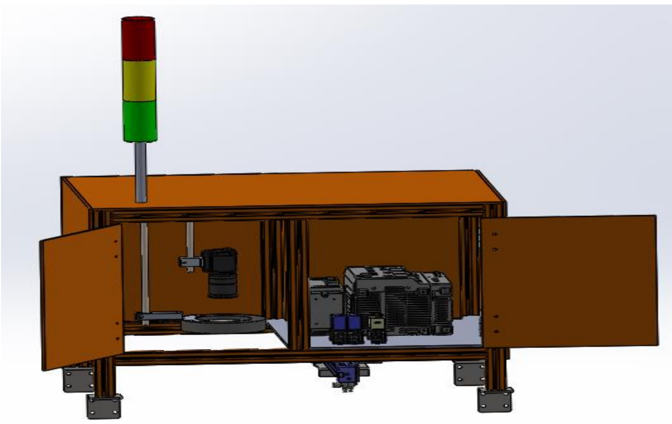

Figure 7: The control box

The dimensions for the control housing box design are given below:

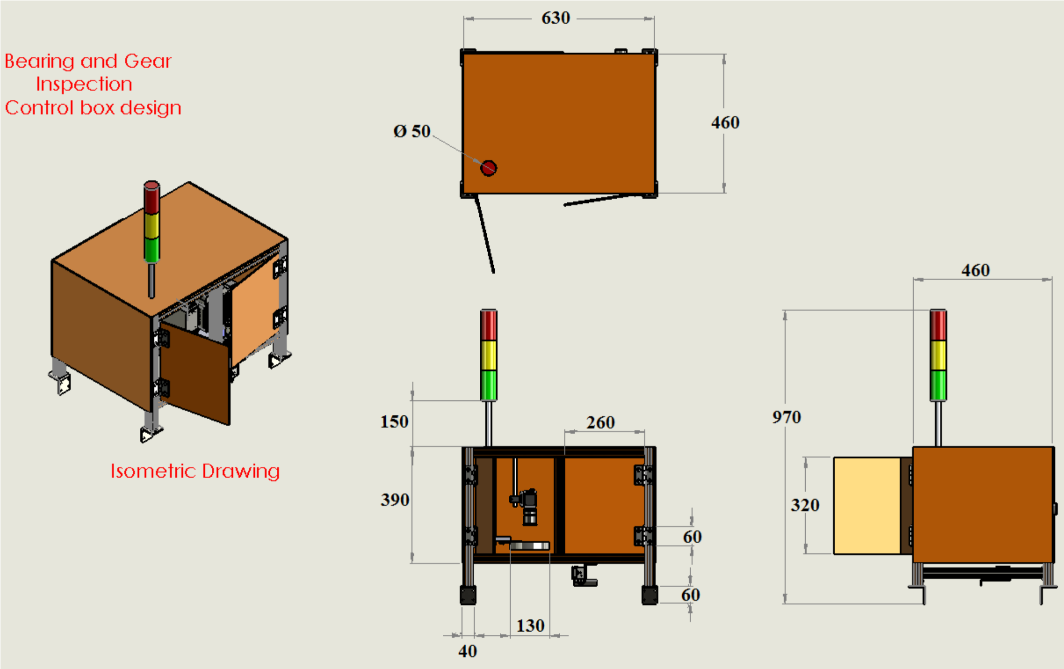

Figure 8: Control box housing design

4.3 The camera platform

The camera platform supports the camera in an elevated position, while at the same time providing a viewing angle of 90 degrees to the component being scanned. The camera is held with adjustable fasteners for the calibration of the viewing angle.

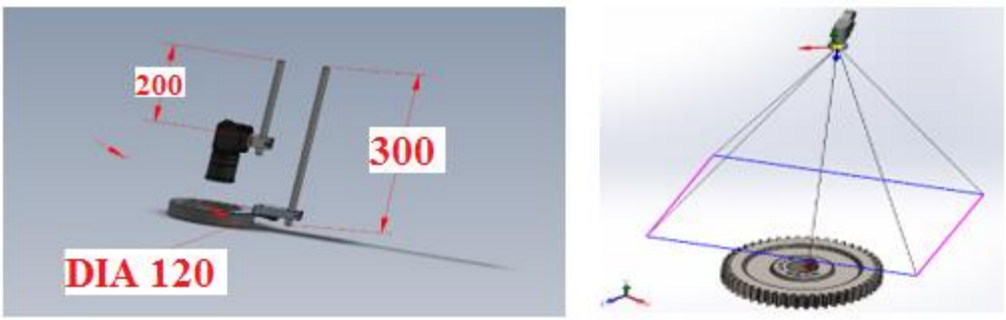

Figure 9: Camera support platform

4.4 Electrical domain

The control circuit was designed to facilitate the automation of the detection system and the conveyance system. It is shown in Figure 10 below:

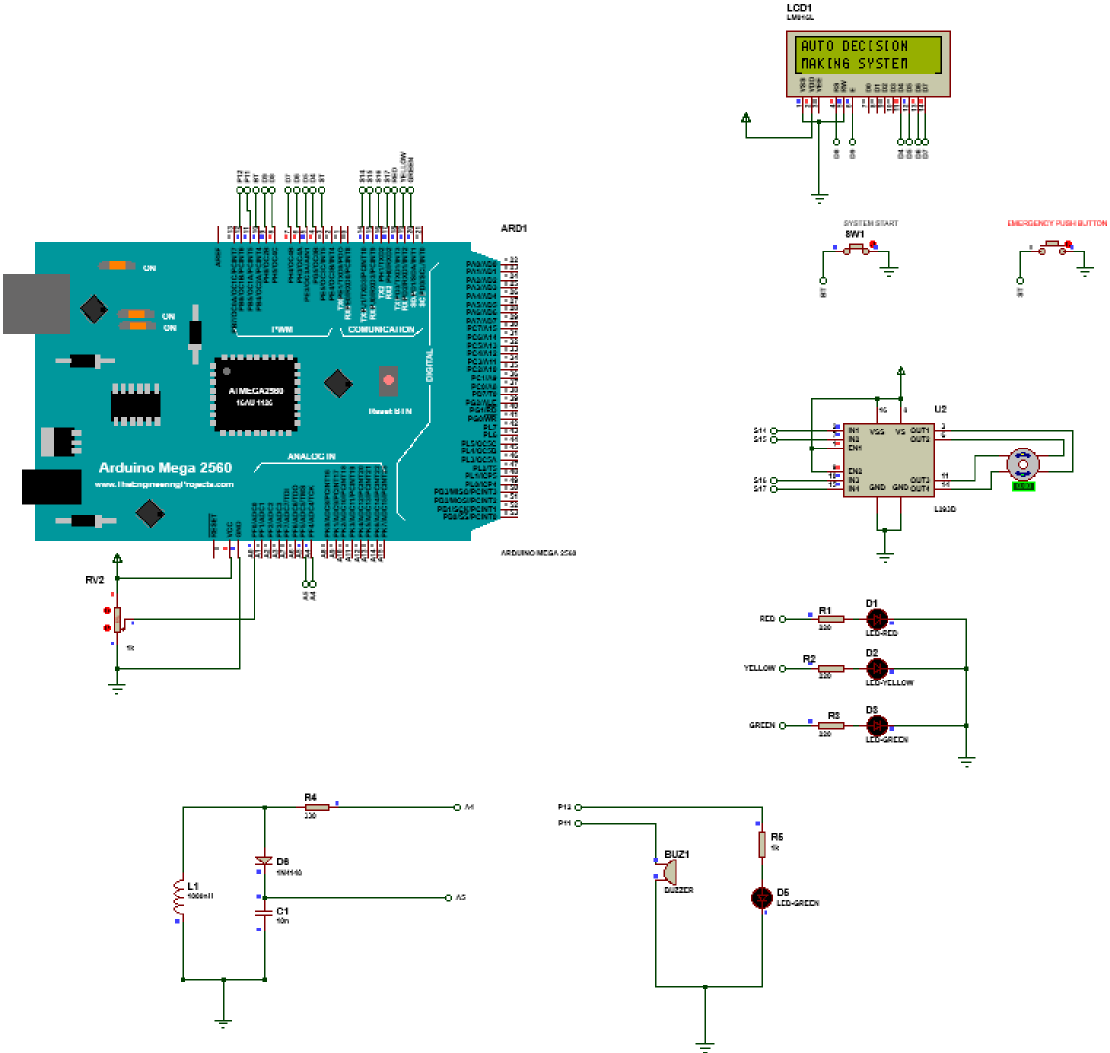

Figure 10: The control circuit

4.5 Image processing

In order for the system to recognise worn-out bearings or gears, the development of algorithms to facilitate software processing is of paramount importance. Machine vision learning is done in cooperation with MATLAB code generation capabilities. The software development follows these stages before processing the images:

i Object identification and recognition (size, base length, number of teeth).
ii Image segmentation and morphology (region analysis, texture analysis, pixel and image statistics).
iii Matching registration estimation (feature-based registration techniques automatically detect distinct image features such as sharp corners, blobs, or regions of uniform intensity).

Figure 11 below shows the MATLAB app system design user interface.

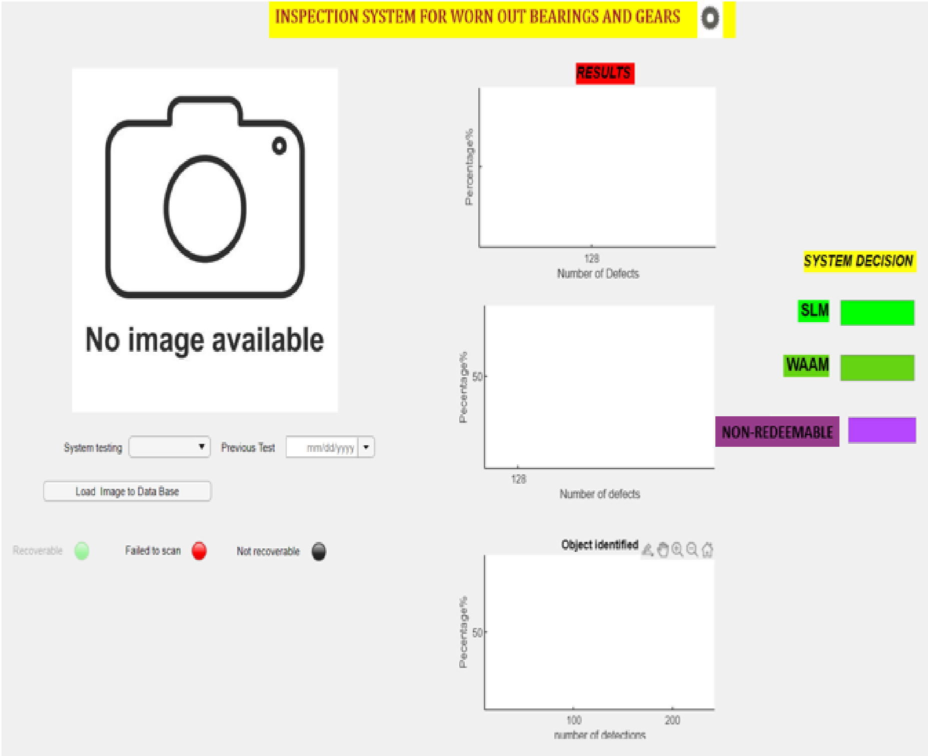

Figure 11: MATLAB app system design user interface

This reveals whether or not the worn-out bearing or gear is redeemable and, if it is redeemable, which manufacturing process would be best.

5 RESULTS AND DISCUSSION

Two pieces of equipment — an involute spur gear and a pillow bearing of the same size but with different material properties — were analysed. The analysis of the bending stresses of the model was done statically with all the pre-processing steps; the initial effects of the static analysis are shown in Figure 12 and Figure 13 below:

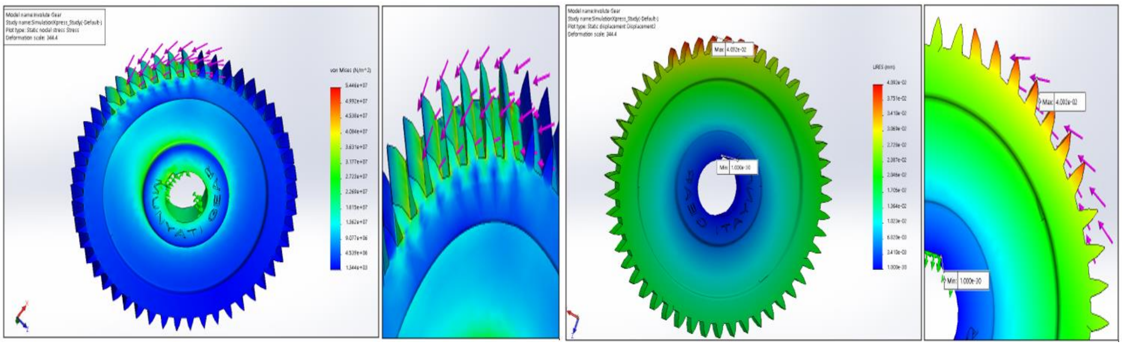

Figure 12: Bending stress applied to involute gear

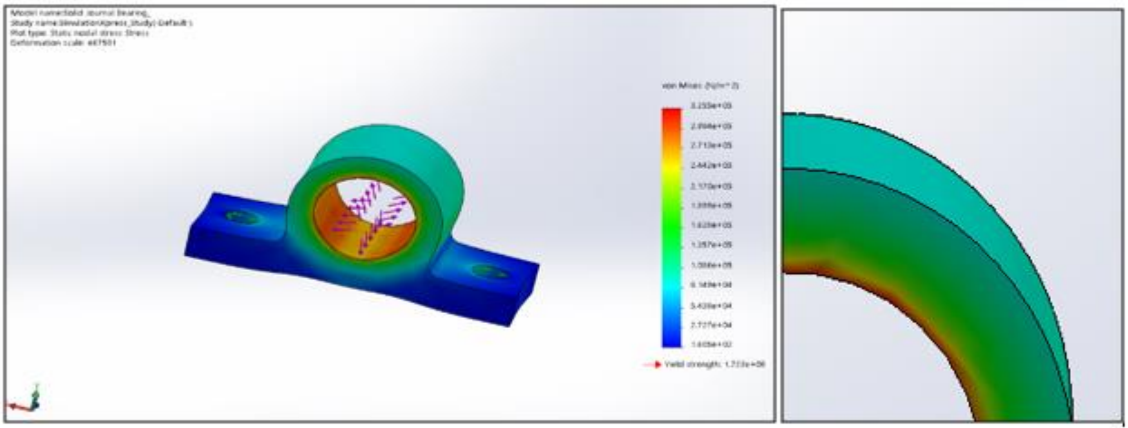

Figure 13: Solid pillow bearing under stress

Different materials were applied to the model such as titanium alloys, nickel and cobalt-based superalloys, and stainless steels. The assumption made during the simulation was that a typical gear meshed with another gear, and so the contact stress on the meshed teeth contributed to the deformation. The resulting deformations after applying a 955N force to the gear teeth had the same deformation patterns. As a result of this force, the gear teeth are most likely to bend or break.

By using image processing, the basic work was carried out to do two of the most important things:

1. To measure the area of the gear image object.
2. To count the number of teeth in the gear image object.

In this regard, the original gear image object was converted to grayscale, and then the grayscale of the original gear image was used to count the teeth of the gear or to analyse the shape or size of the object. This is illustrated in Figure 14 below:

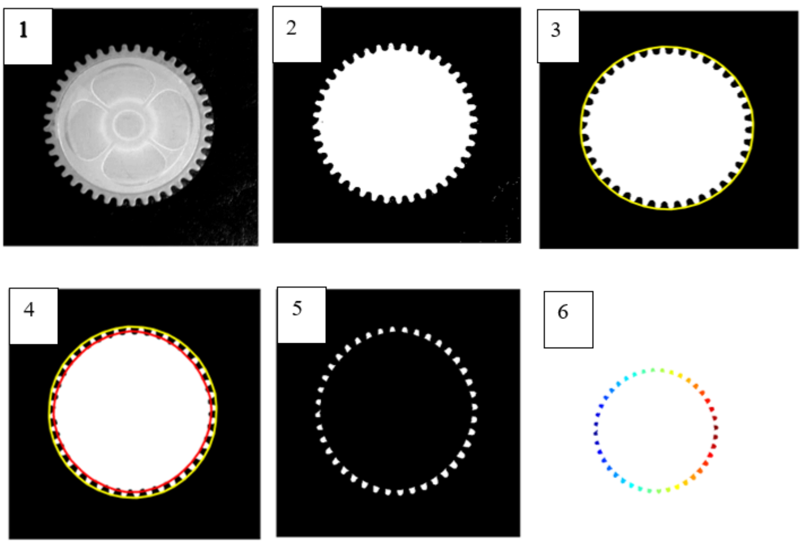

Figure 14: Healthy involute spur gear

This is the gear that is used as the standard with which the deformed gear is compared. The parameters are:

1. The number of gear teeth.
2. Deformation and surface uniformity.
3. Gear size.

These are compared with the original healthy gear. This helps to determine the level of deformation and whether it can be redeemed. Figure 15 below shows the matching worn-out gear.

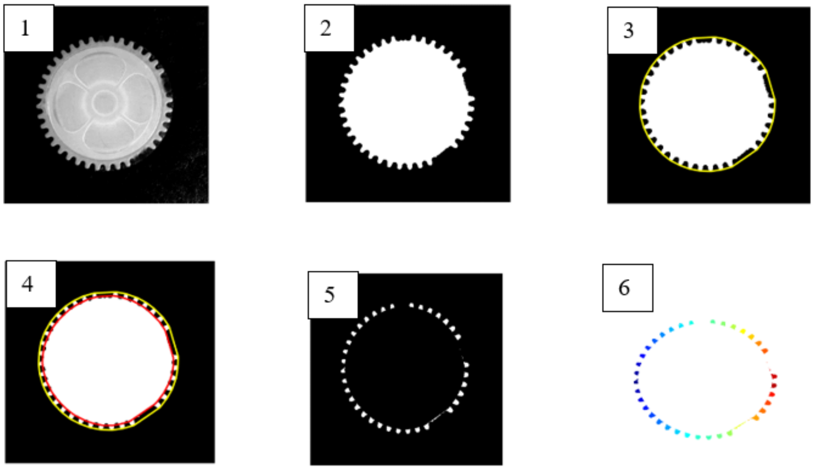

Figure 15: Matching worn-out gear

From the above images, the registration estimator matching algorithm is able to process the missing teeth on the defective gear. The output in image number 6 is the final processing; thus the number of teeth is calculated by counting the coloured pixelated regions. The system goes on to evaluate the redeemability of the deformed gear. This is shown in Figure 16 below.

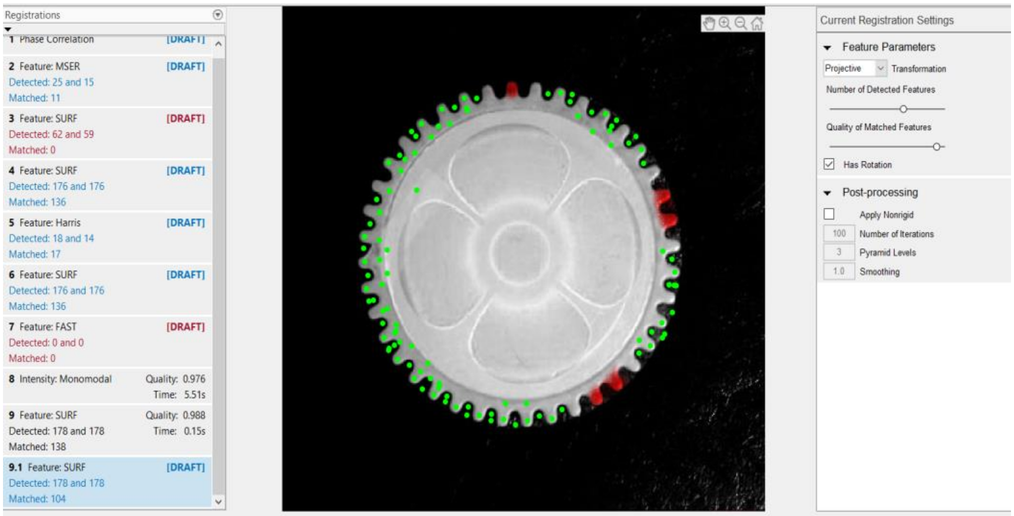

Figure 16: Registration estimator matching algorithm (speeded-up robust features)

Redeemability is based on the non-redeemable percentage. Based on the calculations on parameters such as direct material, direct labour, and direct overheads, it was calculated that the percentage value that determines whether or not the part is redeemable is 40%. If the non-redeemable percentage is below 40%, then it is more economical to redeem the gear or bearing than to buy a new one. Figure 17 shows the pre-processing and image registration in which the decision-making process is made.

From the diagram, it can be seen that the non-redeemable percentage is 4%. Therefore, the decision is that the gear can be redeemed. The next stage is to compare the manufacturing processes based on manufacturing cost. SLM and WAAM are compared in order to select the best manufacturing method, based on total manufacturing cost per method. The method that has the highest percentage is the most economical. The results show that SLM has 94.3% while WAAM has 23.5%. The system automatically selects SLM as the manufacturing method.

Figure 18 shows the decision-making process for the pillow bearing.

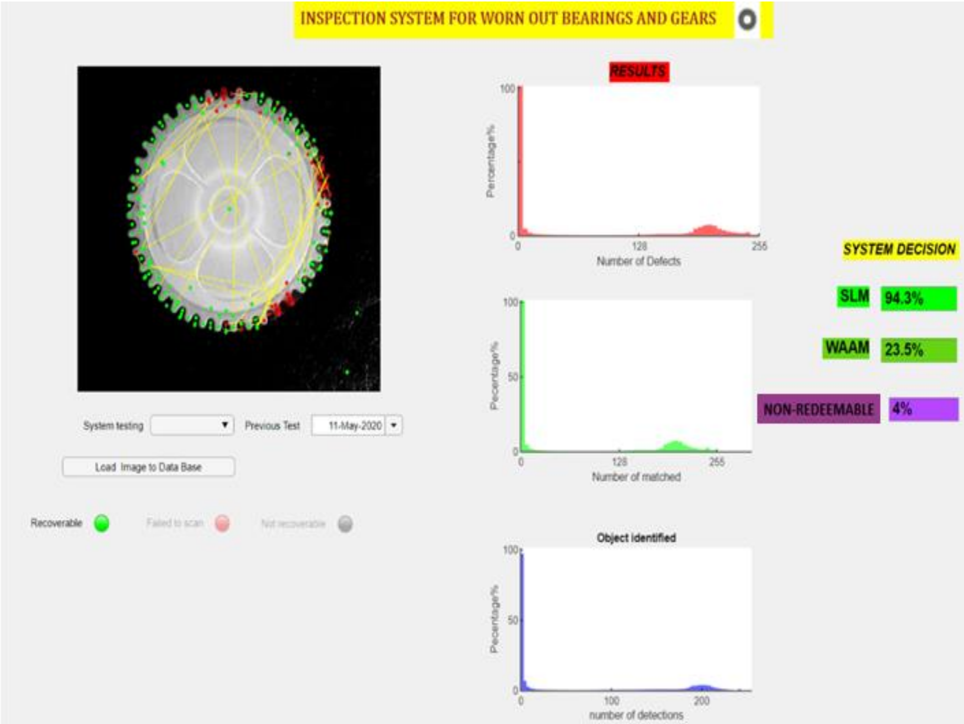

Figure 17: Pre-processing and image registration

Figure 18: Registration estimator using SURF technique

The non-redeemable percentage is 60.2%. This is more than the 40% cut-off mark, and so the pillow bearing is non-redeemable, and has to be replaced.

6 CONCLUSION

The decision-making system that was developed and the results that were obtained highlighted the use of image processing to make decisions. Instead of relying on human inspection, machine learning algorithms were used to develop a system that is able to determine whether a worn-out gear or bearing is redeemable. In the event that it is redeemable, the system determines the best process to be used. The test on a worn-out gear showed a non-redeemable percentage of 4%. This meant that it was more economical to redeem it than to replace it. The SLS and WAAM methods were compared to determine the optimum manufacturing method. SLS, which had 94.3%, was the optimum process when compared with WAAM, which had 23.5%. The bearing, on the other hand, showed a non-redeemable percentage of 60.2%. This meant that it had to be replaced.

The automated process of inspecting is advantageous because decisions are quickly arrived at, eliminating any room for error. The implementation of the design will save money and time because it prevents the unnecessary procurement of equipment to replace defective items. It will also reduce the environmental impact of heavy metals by reducing the amount of scrap metal in the scrapyards.

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