

Artificial Intelligence Based Quality Assurance of Surface Finish of Parts in Assembly Line

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ABSTRACT: Surface finish of machine parts is of considerable importance as it is included in the design and manufacturing of products to meet customers' satisfaction. Above all it may be a major requirement for lapping, close and tight contact to prevent leakages or to minimize stress concentration. In light of the above a system was designed and the algorithm written in python programming language to determine the surface finish of parts in an assembly line. To realize this a dataset of 1800 images of metal surfaces was obtained. The defects were classified into six possible groups: patches, scratches, pitted, rolled and inclusion with 300 images of metal surfaces for each defect.. 1620 images were used in training set and 180 images in the test set. The images were trained and augmented so as to extract the textural features from the images. The images yielded to training. Training accuracy and error were obtained which validates the performance of the dataset during training. The model was also validated by testing it with a different dataset, and its performance established. The accuracy of the system was obtained by dividing the number of correct predictions by the total number of predictions made. The accuracy of the system was 98%, showing the efficiency of the system. It was also established that Artificial Intelligence based method of surface assurance, was more efficient than the contact process – which involve use of profilometer. The accuracy shows the level of conformance of the surface finish test of the parts during assembly line with the laid down specifications during product design. This system is recommended for commercialization and application in industries.

KEYWORDS: Artificial intelligence, quality assurance, surface finish, roughness, parts, assembly line.

1.0 INTRODUCTION

The development of any nation hinges on the vibrancy of the production sector of such nation. However, production entails a detailed step by step process that converts raw or input materials to products. However, for a product to be competitive in the market, it must be designed to ensure that the associated cost of material, manufacturing and storage to be as low as possible. Production has as its first step, the design process, followed by the production of parts then assembly of parts, testing and inspection.

Furthermore, this processes are rather a long iterative demands than theoretically depicted, as several mechanisms have to be put in place and triggered to ensure that products of manufacturing process conforms to the laid down specification.

From the above discuss, it is pertinent to note that conformance in this sense can only be achieved through quality assurance, which is a built-in process.

Furthermore, it is noteworthy that while ensuring that the manufacturing processes and factors are controlled to give the desired output, it is germane that checks be done in assembly-line to ensure non-conformant parts are detected and remedied so as to ensure competitiveness of the product in the market. This is geared towards ensuring product's quality is

maintained in all the parts that make up the product and the final product quality should meet the quality requirement as stated in the quality specification during design.

More so, quality assurance is a part of quality management focused on providing confidence that quality requirement will be fulfilled [1]. However, one of the first thing that offer customers the first sight at the quality is the aesthetic appeal of the product which is determined by the quality of surface finishing of the product. Hence, quality finish becomes the first quality consideration a customer makes before considerations on other factors are made. A product should not be produced with greater accuracy than the service requirement demands. A good design often includes consideration on the finishing or coating operation because a product is judged for appearance as well as on the basis of function and operation.

Furthermore, according to [2], surface finishing describes a variety of manufacturing processes which all improve the aesthetic appearance, material strength and other properties of the finished product. Surface finishing may be achieved by adding, altering, removing or reshaping of materials which may be through mechanical, chemical or electrical means [2]. Additionally, the choice of surface finishing process is influenced by a lot of factors. The factors to be considered

while choosing surface finishing methods are aesthetics demands, removal of defects, improvement on electrical and mechanical properties and environmental considerations. Surface finish offers the first dip at quality which must be consistent in all the parts making up the product. Rough surfaces pose dangers of corrosion; wear as a result of friction which goes on to affect the product performance and hence reducing its useful life. However, in order to ensure that products perform well during service life, it becomes important to ensure that parts are given better surface finish. This helps in avoidance of product liability lawsuits that would have arisen due to defect and injuries.

However, surface finish can be defined in terms of deviation of the surface from a perfectly flat surface which ideally is a true plane [3]. Surface finishing is defined by the waviness and roughness of a surface with respect to a perfectly flat surface. This waviness or roughness is calculated as a mean, and hence, useful deductions hereto made.

However, in order to achieve consistency in surface finish, and other material property, the need to ensure variability from the laid down surface finishing requirement be eliminated as much as possible. From the foregoing, it becomes needful that control measures should be put in place to ensure detection and remediation of non-compliant parts in order to eliminate cases of poor quality and liability lawsuits. More so, there exist different approaches where the surface finish could be controlled. These are use of Genetic Algorithm, use of computer vision, use of Artificial Neural Network and Fuzzy Logic.

However, I will in the course of this study discuss these methods in the literature section, but will be working with the convolution neural network.

Surface finish is a very important aspect in production which forms an important consideration in product quality assessment. However, though quality should be a built in process, there is need for the final quality check to be carried out during assembly to test whether the different parts have conformed to the quality specification as stated during product design.

However, the conventional method involves physical examination of parts to assess whether they have met the laid down specification. The process is however tedious, time consuming and inefficient. In order to ensure maximization of profit, it becomes important that the time spent in quality checks be reduced.

On this note, it becomes needful for incorporation of control mechanisms through the use of artificial intelligence which ensures reduction in production time and involvement of special skill personnel.

Furthermore, various approaches abound which are genetic algorithm, fuzzy logic, artificial neural network and computer vision. This work proposes to use Convolution Neural Network to check surface finish of a part.

The objective of this research is to use Artificial Intelligence in checking surface finish of a part..

It is well known that the existent process employed for quality check in industries deals with physical examination of parts. This process is however time consuming, ineffective, which invariably leads to increase in production cost due to material handling, idle time and queuing.

Additionally, the approach is ineffective, and cannot guarantee quality delivery. In a market that is leaning towards high product quality at reduced cost, it becomes important that production time be reduced by taking away ineffective time and process. Hence, the need to incorporate artificial intelligence into the process in order to ensure efficiency while reducing the production cost. The research work will use the basic principle of convolution neural network. It will thereafter develop a model wherewith rough surfaces could be detected easily by comparing it against the dataset. Its efficiency will be established and recommendations made.

1.1 The Assembly Process

There have been discussions on the use of artificial intelligence in ensuring quality assurance of surface finish, but are however theoretical and largely experimental.

Assembly involves putting of different parts together in order to perform a combine function expected of the system or product as stated during product design specification.

However, the assembly component ranges from individual parts to sub-assembly which behave as a single unit when put together.

Assembly system is one of the sub-systems in manufacturing system where the individual components of a product are joined together and thus integrated into a semi-finished or into a finished product[4].

However, assembly is an important aspect of production, hence, its consideration during design. This concept is known as design for assembly.

Furthermore, a broader approach that is usually employed in production is design for manufacture, which is a holistic approach to production of goods which integrates the product design process with material selection, consideration of manufacturing methods, process planning, assembly, testing and quality assurance.

However, design for Assembly being a sub-set of design for manufacture considers the ease, speed, and cost of putting parts together.

Additionally, design for assembly simplifies the product so that the cost of assembly is reduced. Further, it helps in reduction in production of equipment and part inventory [5]. Design for Assembly (DFA) may be defined as a process for improving product design for ease and low cost assembly, which is achieved by means of concurrent focus on the dual aspect of functionality and ease of assembly [6].

However, assembly can be done through manual, automated and robotic means.

Manual assembly line consist of a sequence of workstation where products are assembled by human workers, by adding components which progressively build the product as they move along the line [5].

Automated assembly line involves the use of mechanized and automated device to perform the various assembly tasks in an assembly line or cell [5]. Automated assembly line is employed where there is high product demand. Automated assembly system can be classified based on either the type of work transfer system or based on the physical configuration. Furthermore, based on the type of work transfer system, automated assembly can be classified as: synchronous transfer system, asynchronous transfer system , stationary transfer system

The first three systems above deals with same method of system transfer, while the last, being stationary transfer system involve the transfer base being in one place, while parts are being added to it.

Automated transfer system can also be grouped based on physical configuration as: dial type assembly machine, in-line assembly system, carousel assembly system, single-station assembly machine.

The dial type assembly system has the work station located on the outside periphery of the dial. However, as the table rotates, components are being added to the base parts at each workstation.

In-line assembly is designed to have the workstations in a straight line arrangement.

Carousel assembly system is a hybrid class obtained by a compromise between circular flow of dial and the In-line system of assembly.

Single station, as the name suggest is the type of assembly system where assembly operations are done in a single location - by continuously adding components to the base part until a finished product is obtained.

More so, in Robotic assembly line, industrial robots are used in assembly operation. Robotic assembly line is used where there is high product demand compared to manual but lower than that of automated assembly line.

However, parameters to be considered when choosing the type of assembly are cost, volume and the efficiency of the process.

It should be noted that quality is a built-in process which demands checks at every stage of production to ensure that the product produced conforms to the quality specification.

From the foregoing, it becomes germane that checks be done during assembly to ensure that the different parts or components conform to the laid-down quality.

1.2 Quality Assurance and Control in Assembly System

Quality is a management method that is defined as all those planned and systematic actions needed to provide adequate confidence that a product, service or result will satisfy given requirements for quality and be fit for use [7].

A quality assurance programme is defined as the sum total of the activities aimed at achieving that required standard [7].

However, quality control is a reactionary process that verifies if the part or product has conformed to the quality specification. Quality control is a reactive part of quality assurance management.

However, during assembly, it is necessary for checks to be done, not only to appraise the effectiveness of the quality assurance management in use, but in ensuring that non-conformant parts are detected and appropriate remediation measures triggered to ensure remediation of the defective part.

Quality control in assembly could be done in two broad approaches. These are visual examination and the use of artificial intelligence. Visual examination process involves physical appraisals by humans to ensure the parts are of acceptable quality. On the other hand, artificial intelligence could be employed where a pass or fail judgement could be passed on parts on assembly line and hence, could be employed where high product volume is needed.

However, in order to have an effective quality control measures, one must: define the quality standard of the product(s), select the quality control method to be adopted ,establish the number of products or batch to be tested , train employees on the approach, put in appropriate remediation method in place to remedy defects..

However, during inspection, product inspectors are normally provided with lists and description of unacceptable product defects such as cracks, surface blemishes for example [8].

Additionally, it is noteworthy that for the purpose of this study, I will restrict myself to quality assurance on surface finish.

1.3 Codes and Standards in Quality Control

Standard is a measure of the level of quality, where all other outcomes must conform. Standard is a benchmark for quality management.

However, there are codes and standards in engineering practices which governs quality measurement. These codes and standards are established, regulated and enforced by the international organization for standardization (ISO), a non-governmental organization comprising of standard bodies from over 160 countries of the world.

The International Organization for Standardization develops and publishes international codes and standards in other to meet market demands.

However, according to American society for quality, quality standards are defined as documents that provide requirements, specifications, guidelines or characteristics that can be used consistently to ensure that materials, products, processes and services are fit for their intended purpose. The quality of an organization is the degree to which the inherent characteristics of the organization fulfills the needs and expectations of its customers and other interested parties, in other to achieve sustained success (ISO).

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Furthermore, standardization enables organization to have shared visions, understanding, procedures and vocabulary needed to meet the needs of the stakeholders (ASQ). According to American Society for Quality, quality Standards aims to fulfill the following objectives; satisfying their customer’s quality requirement, ensuring their products and services are safe, complying with regulations, meeting environmental objectives, protecting products against climatic or other adverse conditions, ensuring that internal processes are defined and controlled, more so, the quality management standards and codes.

This quality specification goes with the code BS EN ISO 9000. According to international organization for standardization (ISO), ISO 9000 defines the fundamental concepts and principles of quality management which are universally applicable to the following;

- (i) Organizations seeking sustained success through the implementation of a quality management system

- (ii) Customers seeking confidence in an organization’s ability to consistently provide products and services.
- (iii) Organizations seeking confidence in their supply chain that their products and service requirements will be met.
- (iv) Organizations and interested parties seeking to improve communication through a common understanding of the vocabulary used in the quality management.
- (v) Developers of related standards.

ISO 9000 [9] specifies the terms and definitions that apply to all quality management system standards developed by ISO/TC176 (ISO).

However, ISO 9000 series are based on seven quality management principles (ISO). The principles are as represented in the Table 1.

Table 1: Quality Management Principles (ISO 9000)

Quality Management Principle	Approach	Definition
1	Customer focus	Organization depends on their customers and therefore should understand current and future customer needs, should meet customer’s requirements and strive to exceed customers’ expectations.
2	Leadership	Leaders establish unity of purpose and direction of the organization. They should create and maintain the internal environment in which people can become fully involved in achieving the organization’s objectives.
3	Engagement of people	People at all levels are the essence of an organization and their full involvement enables their abilities to be used for the organization’s benefit.
4	Process approach	A desired result is achieved more efficiently when activities and related resources are managed as a process.
5	Improvement	Improvement of the organization’s overall performance should be a permanent objective of the organization.
6	Evidence - based decision making	Effective decisions are based on the analysis of data and information.
7	Relationship management	An organization and its external providers (suppliers, contractors, and service providers) are interdependent, and a mutual beneficial relationship enhances the ability of both to create value.

Source: [9]

This quality requirement goes with the code EN BS ISO 9001. ISO 9001 focuses on ensuring that the products and services are of the best quality. It specifies requirements for a quality management system (QMS).

According to Swiss Approval international, the organizational process of a company which applies ISO 9001 as well as related quality management system principles and

requirements follows a plan–do–act approach, which stipulates a 4 phase PDCA cycle AS:

Plan: The overall responsibility for the applied management system must be assigned to the top management. A quality officer and a quality team should be appointed. Furthermore, the organization has to formulate the quality policy in a written statement which describes the intentions and direction

of the Management policies as well as its Commitment to Quality. The Quality Policy must be communicated within the organization. The quality team is the connection between the management and employees. In this phase, the organization has to identify the significant processes and prioritize the opportunities for the enhancement of customers' satisfaction and for the continuous improvement of its operations' performance.

Do: The stated objectives and processes are now introduced and implemented. Resources are made available and responsibilities determined. Make sure that employees and other participants are aware of and capable of carrying out their quality management responsibilities. The realization of the quality management system begins.

Check: A quality management system requires a process for compliance and valuation of legal-related regulations. Internal audits can help to verify that the management system operates properly and generates the planned results. The processes are monitored with regards to legal, products' and services' specifications or other requirements (customer requirements, internal policies) as well as to the objectives of the quality management of the organization. The results are documented and reported to the top management.

Act: Top management prepares a written evaluation summary based on the internal audit reports. This document is called management review. The results will be evaluated on their performance level. If necessary, corrective or preventive actions can be initiated. Operations-related processes are optimized and new strategic goals are derived and being set. This quality specification goes with the code EN BS 9004. ISO 9004 is a guideline beyond the requirements given in ISO 9001 in order to consider both the effectiveness and efficiency of a quality management system and consequently the potential for improvement of the performance of the organization (ISO). When compared to ISO 9001, the objective of consumer satisfaction and product quality are extended to include the satisfaction of the interested parties and the performance of the organization. ISO 9004 provides

guidance to support the achievement of sustained success by a quality management approach, and it is applicable to any organization, regardless the size, type and activity (ISO). In simple terms, ISO 9004 provides guidance to any organization on ways to make their quality management more successful [10].

1.4 Surface Finishing

Surface finish involves the process of altering a metal's surface by adding, removing or reshaping (Huang, 2021). These measures are used to ensure a smooth surface, great accuracy, aesthetic appearance or protective coating. Surface roughness is typically measured perpendicular to the lay direction by an instrument known as profilometer [11]. The relation between roughness and smoothness of a component's surface is called surface finish [12]. Since surface finishing is a product of machining operation, it follows that surface finish has a direct correlation the type of machining operation used, tool and other machining parameters. Surface roughness occurs as a result of poor choice of cutting speed, feed rate and depth of cut - with the result being localized irregularities of the surfaces of the material. I will at this juncture state here that some applications need close tolerance which demands that parts be produced as close to the design specification as possible. Hence, in such cases, it becomes necessary that checks be put in place to ensure that the surfaces are smooth and close to the laid-down dimensions as possible.

Also, a good finish ensues a minimal resistance between the two moving parts and wear between such moving parts is also minimal, hence such parts have longer life and less unexpected failure rate during continuous operation [12]. Other properties such as heat transmission, light reflection, holding lubricant are also affected due to quality of machined surface of a part[12] . Figure 1 shows the surface finish profile, while Figure 2 shows the roughness and waviness profile of a surface.

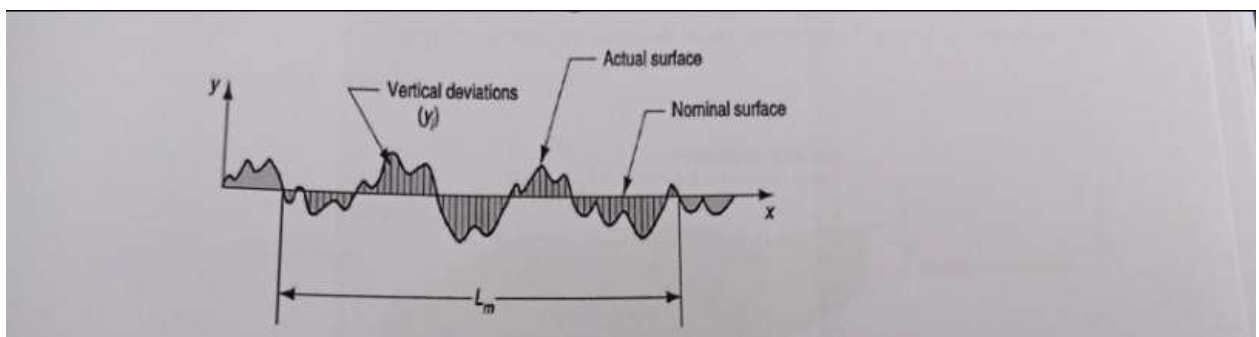


Figure 1: Surface finish profile[13]

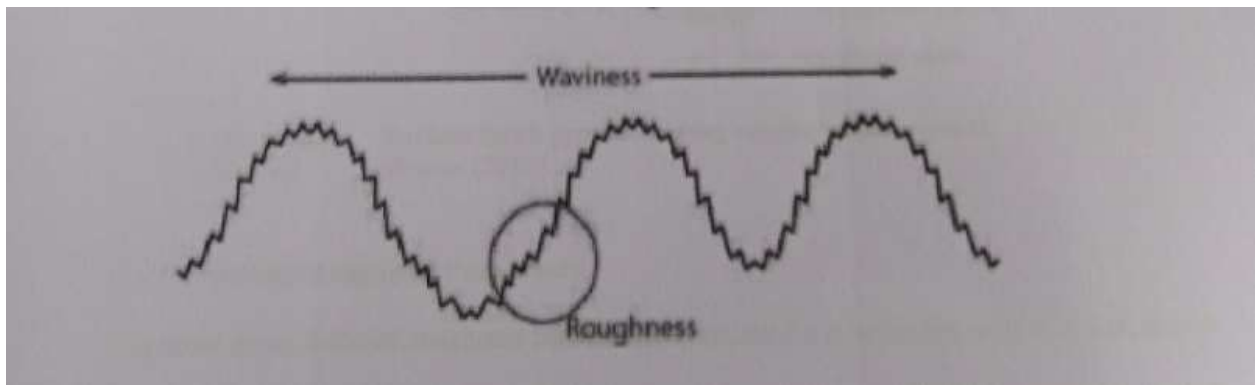


Figure 2: Surface finish profile showing waviness and roughness[13]

Surface finish parameters can be categorized into roughness waviness and form. Surface Roughness or simply roughness is a measure of the total spaced surface irregularities [14]. Surface roughness is measured using either a contact type meter or non contact type process. Contact process involves tracing the stylus profilometer (Stylus probe meter) on the surface of the material to be measured. The non contact process involves the use of light in place of stylus.

Form can be defined as the general shape of the surface, if waviness and roughness were to be non-existent or ignored. However, surface finish of a given material may be defined by either of Form, waviness or roughness or a combination of two or three of these elements. Figure .3 shows surface roughness parameters.

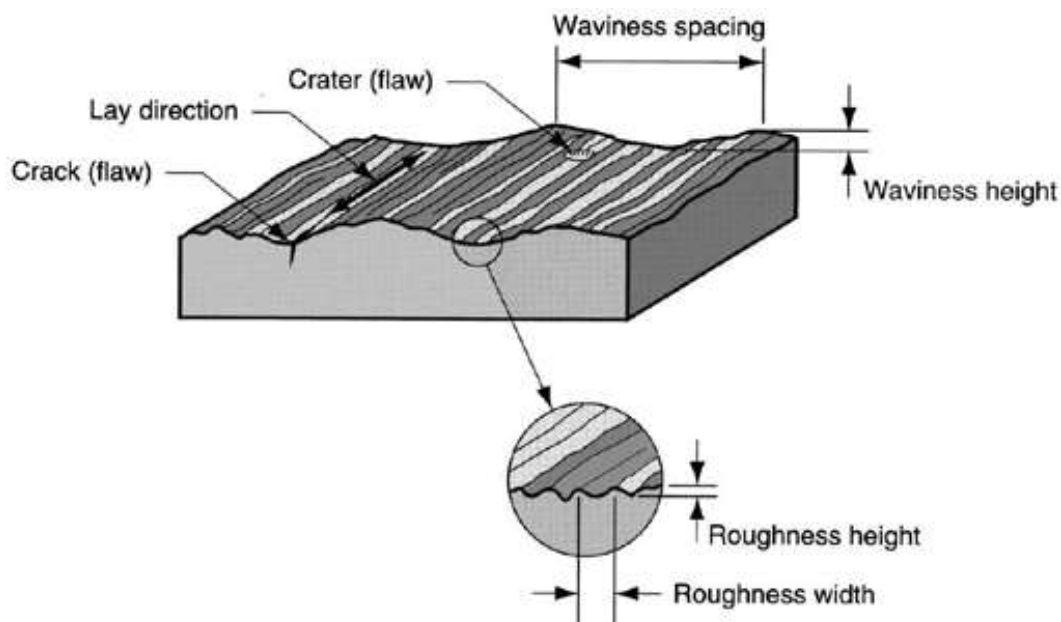


Figure 3: Surface finish profile showing roughness parameters[13]

Source: Sharma (2015).

1.5 Surface Roughness Parameters

There are many different roughness parameters in use, but Ra is by far the most common, though this is often for historical reasons and not for particular merit, as the early roughness meters could only measure Ra (Abbot). Surface Parameters can be classified into Amplitude parameters spacing parameters and hybrid parameters. Amplitude parameters mostly measures surface deviations in terms of the vertical characteristics. Examples are;

- (i) Roughness Mean Arithmetic value (Ra): This measures the departure of roughness profile from the mean line

$$Ra = \frac{1}{l} \int_0^l [z(x)] dx$$

Equation 1

where $z(x)$ is a roughness profile of length l .

- (ii) Roughness root mean value (Rq)

$$Rq = \sqrt{\frac{1}{l} \int_0^l z^2(x) dx}$$

Equation 2

- (iii) Maximum profile valley depth (Rv) is the maximum depth of the profile below the mean line within the evaluation length.

$$Rv_i = |\min z(x)|$$

Equation .3

$$Rv = \sum_{i=1}^n Rv_i$$

Equation .4

where: Rvi is the maximum debts of profile below the mean line.

Spacing Parameters: These parameters define surface in terms of the distance. These parameters are:

- (i) Mean Spacing (Rsm): This is the average spacing between profile elements at the mean line within the chosen length.
- (ii) Peak Count (Rpc): Is the number of roughness profile peaks per unit distance that projects above the mean line.
- (iii) High Spot Count (HSC): Is defined as the number of high regions of the profile above the mean line or above the line parallel to the mean line per unit length along the assessment length [15].
- (iv) Mean spacing of Adjacent local Peaks (S): this is the mean spacing of adjacent local peaks of the profile measured along the assessment length[15].
- (V) Hybrid Parameters: Hybrid parameters combine spacing and amplitude parameters.

1.6 Evaluation of Surface Roughness

The methods basically employed are:

- (i) Centre line Average (CLA): This involve the use of mean line which is drawn in the direction of the surface profile. As the name implies, it is the average which means the area above the line and the area below the line is approximately equal. The average height can thus be calculated as the summation of all area above and below the line divided by the sampling length. These are seen in Equations 5, .6, and 7 respectively [16].

$$Ha = A/L = ((A+A+A) + (B+B))/L$$

Equation 5

$$CLA = HA (VXH) \times 1000 \mu m$$

Equation .6

$$Ra = \frac{\{(A+A+A) + (B+B)L\} \times 1000 \mu m}{L}$$

Equation .7

where; A and B are portions above and below the mean line respectively.

- (ii) Root Mean Square Method: it is a geometrical average of the ordinates of the profile about the mean line [16]. According to Amrit, if n measurement are made from the mean line above and below to the points on the surface profile.
- (iii) Ten Points Heights Method: This measures the average difference between the fine highest peaks and the fine lowest valleys of surface texture within the sampling length measured from a line parallel to the mean line and no crossing the profile. Table 2 shows the interpretation of roughness symbols.

Table 2: Interpretation of Roughness Symbols

BASIC SURFACE TEXTURE SYMBOL	MAXIMUM WAVINESS SPACING RATING (C). SPECIFY IN INCHES OR MILLIMETERS. HORIZONTAL BAR ADDED TO BASIC SYMBOL.
ROUGHNESS AVERAGE VALUES (A). SPECIFY IN MICROINCHES, MICROMETERS, OR ROUGHNESS GRADE NUMBERS.	LAY SYMBOL (E)
MAXIMUM AND MINIMUM ROUGHNESS AVERAGE VALUES (A), SPECIFY IN MICROINCHES, MICROMETERS, OR ROUGHNESS GRADE NUMBERS.	ROUGHNESS SAMPLING LENGTH OR CUTOFF RATING (D). WHEN NO VALUE IS SHOWN USE .03 INCH (0.8 MILLIMETERS).
MAXIMUM WAVINESS HEIGHT RATING (B) SPECIFY IN INCHES OR MILLIMETERS. HORIZONTAL BAR ADDED TO BASIC SYMBOL.	MACHINING ALLOWANCE (F). SPECIFY IN INCHES OR MILLIMETERS.

NOTE: WAVINESS IS NOT USED IN ISO STANDARDS.

Source: [7]

Table 3 shows roughness parameters and the grading system.

Table 3: Roughness Parameters and Grading

R _a micrometer μ m	R _a micro-inch μ in	Roughness Grade Numbers (New)**	Roughness Grade Numbers (Old)***	R _t	(R _a)	Old Style	American standard
50	2000	N12					
25	1000	N11					
12.5	500	N10					
6.3	250	N9		32		32	250
3.2	125	N8		16			125
1.6	63	N7		8		8	63
0.8	32	N6		4			32
0.4	16	N5		2		2	16
0.2	8	N4		1			8
0.1	4	N3		0.5		0.5	4
0.05	2	N2		0.25		0.25	2
0.025	1	N1					

Source: [7]

Surface parameters can be evaluated by comparing the values obtained with the standard values on the table below. Table 4 shows the international standard organization conversion chart for surface finish.

Table 4: Surface Finish Conversion Chart

Surface Finish Conversion Chart						
N	Rt	Ra	CLA	RMS	Cut-off length	
					Inches	mm
1.	0.3	0.025	1	1.1	0.003	0.08
2.	0.5	0.05	2	2.2	0.01	0.25
3.	0.8	0.1	4	4.4	0.01	0.25
4.	1.2	0.2	8	8.8	0.01	0.25
5.	2.0	0.4	16	17.6	0.01	0.25
6.	4.0	0.8	32	35.2	0.03	0.8
7.	8.0	1.6	63	64.3	0.03	0.8
8.	13	3.2	125	137.5	0.1	2.5
9.	25	6.3	250	275	0.1	2.5
10.	50	12.5	500	550	0.1	2.5
11.	100	25.0	1,000	1,100	0.3	8.0
12.	200	50.0	2,000	2,200	0.3	8.0

N = New ISO scale numbers CLA = Center line average in microinches
Rt = Roughness, total in microns RMS = Root mean square in microinches Ra = Roughness, average in microns

Source: [7]

1.7 Artificial Intelligence

Artificial intelligence is the simulation of human intelligence processes by machines, especially computer systems – including expert systems, natural language processing, speech recognition and machine vision.

Simply put artificial intelligence can be as the theory and development of computer systems able to perform task that normally require human intelligence, such as visual perception, speech recognition, decision making and translation between languages (Oxford English Dictionary). The goals of artificial intelligence research include reasoning, knowledge representation, planning, learning, natural language processing, perception and the ability to move and manipulate objects.

However, the haul mark of artificial intelligence is the use of programmable codes/instruction with the help of computer to simulate human brain and ensure that problems are solved through logical reasoning and execution that mimics human’s brain. Simply put, AI systems work by ingesting large

amounts of labeled training data, analyzing the data, for correlations and patterns, and using these patterns to make predictions about future states(Ed Burns).

However, artificial intelligence can be divided into broad branches which are Machine Learning, Artificial Neural Network, Robotics, Expert System, Fuzzy Logic and Natural Language Processing and speech recognition.

The branches of artificial intelligence are:

- (i) **Expert System:** A system designed to mimic human decision making ability. It is a computer program that uses artificial intelligence processes to solve problems within a specialized domain that ordinarily requires human expertise (Vladimir). Expert systems usually relies on two components – which is a knowledge base and an inference engine – in order to accomplish feats of apparent intelligence [17]. The Figure 4 explains the basic concept of expert systems.

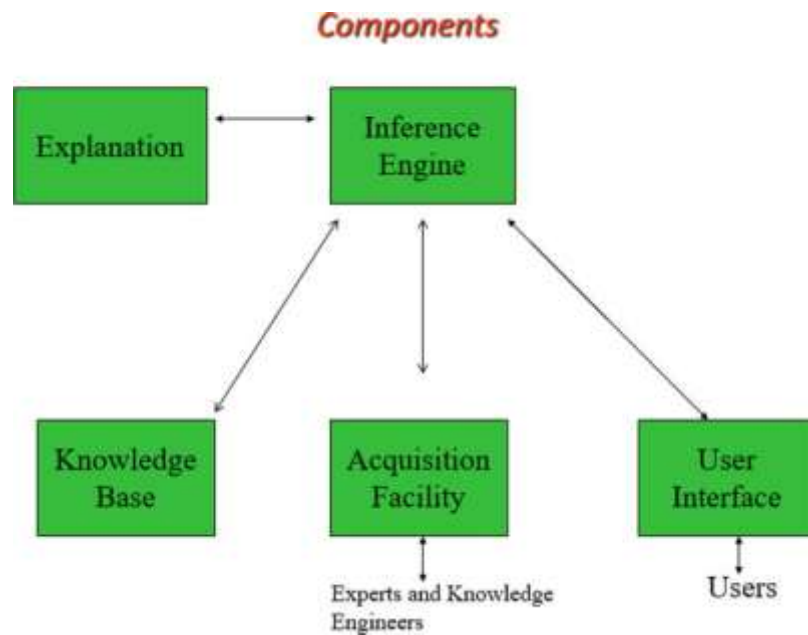


Figure 4: Components of an Expert system
Source: [17]

Furthermore, a knowledge base is an organized collection of facts about the system domain while an inference engine interprets and evaluates the fact in the knowledge base in order to provide an answer [17]. Typical tasks for expert systems involve classification, diagnosis, monitoring, design, scheduling, and planning for specialized endeavours [17]. However, for an expert system to work, the knowledge base must be acquired from human experts. This knowledge is then usually represented in the form of ‘if – then’ rules (production rules): if some conditions are true, then the following inference can be made – or some actions taken [17].

- (ii) **Robotics:** Robotics is an interdisciplinary branch of computer science and engineering. It is a field in artificial intelligence which involve design and construction of robots. Robots are usually employed in task and areas which poses hazards to human health. Many aspects of robotics involve artificial intelligence where robots may be equipped with the equivalence of human senses such as vision, touch, and the ability to sense temperature (Barbara). Most robots are capable of simple decision making, and the current robotics

research is geared towards devising robots with a degree of self-sufficiency that will permit mobility and decision making in an unstructured environment. Robotics finds application in manufacturing in the areas of fabrication, finishing, transfer and assembly of parts. Robotics are also used in material handling, which involve picking, sorting, and packaging of products.

- (iii) **Fuzzy Logic:** Employed where uncertainties abound. As the name suggest, fuzzy logic was a standard logic to establish whether a concept is true or false. Fuzzy logic is an approach to variable processing that allows for multiple possible truth values to be processed through the same variable[18]. Fuzzy logic is designed to solve problems by considering all available information and making the best possible decision given the input (Gordon, 2022). It is employed to handle the concept of partial truth, where the truth value may range between completely true and completely false [19]. The figure below explains the difference between Boolean logic and Fuzzy logic.

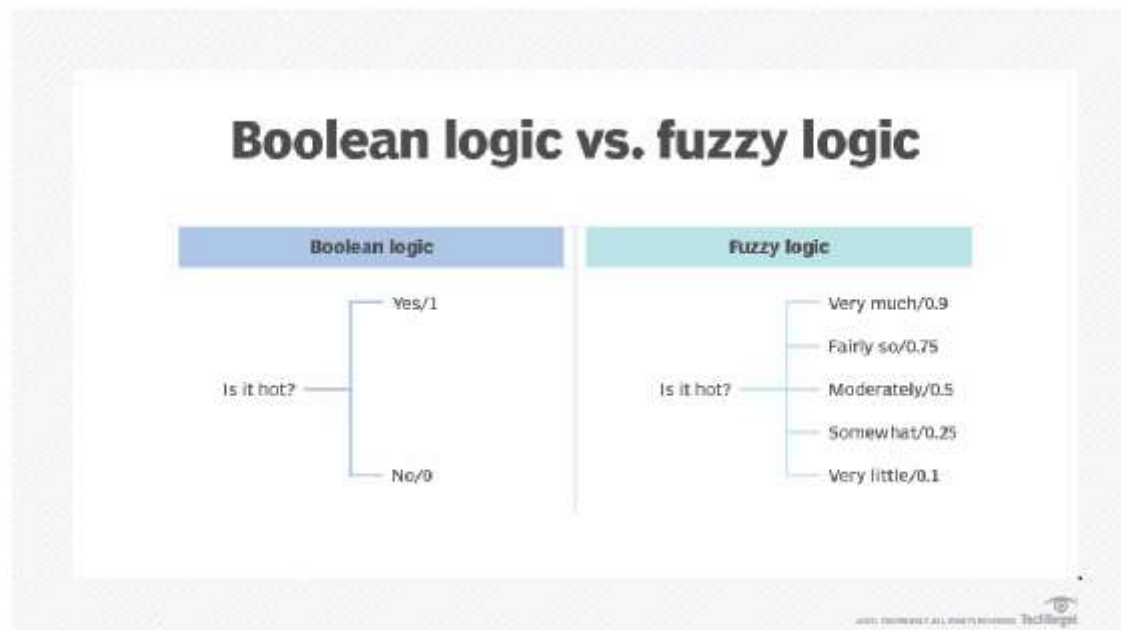


Figure 5: Boolean logic and Fuzzy logic

Source: [20]

Simply put, fuzzy logic computes based on the degree of truth rather than the usual true and false approach of modern computing. In artificial intelligence, fuzzy logic can be used to imitate human reasoning and recognition [20]. Rather than strictly binary cases of truth, fuzzy logic includes 0 and 1 as extreme cases of truth, but with various intermediate degrees of truth [20]. A logic is 1 if it is true and 0 if it is false.

According to [20], fuzzy logic is best suited for the following:

- (i) Engineering for decisions without clear certainties and uncertainties, or imprecise data – such as with natural language processing technologies; and
- (ii) Regulating and controlling machine outputs, according to multiple input/output variables – such as with temperature controlling systems.

According to [20], other applications of fuzzy logic are

Various types of AI systems and technologies use fuzzy logic. This includes vehicle intelligence, consumer electronics, medicine, software, chemicals and aerospace.

In automobiles, fuzzy logic is used for gear selection and is based on factors such as engine load, road conditions and style of driving:

- (i) In dishwashers, fuzzy logic is used to determine the washing strategy and power needed, which is based on factors such as the number of dishes and the level of food residue on the dishes.

- (ii) In copy machines, fuzzy logic is used to adjust drum voltage based on factors such as humidity, picture density and temperature.
- (iii) In aerospace, fuzzy logic is used to manage altitude control for satellites and spacecrafts based on environmental factors.
- (iv) In medicine, fuzzy logic is used for computer-aided diagnoses, based on factors such as symptoms and medical history.
- (v) In chemical distillation, fuzzy logic is used to control pH and temperature variables.
- (vi) In natural language processing, fuzzy logic is used to determine semantic relations between concepts represented by words and other linguistic variables.
- (vii) In environmental control systems, such as air conditioners and heaters, fuzzy logic determines output based on factors such as current temperature and target temperature.
- (viii) In a business rules engine, fuzzy logic may be used to streamline decision-making according to predetermined criteria.

- (iv) **Neural Network:** Synonymous with human brain. It is composed of network of neurons which uses the process of deep learning in learning and executing task independently to achieve its goals. Neural network

model operates in the form of layers which are: the input layer, a hidden layer which is for pattern recognition and the output layer.

(v) **Natural Language Processing:** This deals with ability of machine or computer to read and understand basic human language. This enables machine to convert human sounds to text form and hence help computer in decoding human’s intentions.

(vi) **Machine Learning:** This is a branch of artificial intelligence that enables a machine or a computer to process, analyze and interpret and in using same in providing solutions to real life problems.

Furthermore, the technology employed in machine learning involves training computer data or information for them to be able to recognize such. On recognition of these data, judgement could be passed on it. However, which are supervised learning, unsupervised learning and reinforced learning.

A supervised learning involve training of machine learning algorithm on labeled data and the variables defined in order to enable extrapolations of indices like correlations and mean.

Unsupervised Learning: This involves training of algorithms on unlabelled data wherewith correlations

could be drawn from such data. This takes away the human effort in making the dataset readable.

(vii) **Reinforcement Learning:** It involves the multi-state approach in allowing intelligence agents to take decisions on their own. It is an area of machine learning which borders on how intelligent agents out to take actions in an environment in order to maximize the notion of cumulative reward. Reinforcement learning differs from supervised learning in not needing labelled inputs /output pairs to be presented, and in not needing sub-optimal actions to be explicitly corrected –instead the focus is on finding a balance between exploration (of uncharted territory) and exploitation; which is of current knowledge [21]. The environment is typically stated in the of Markov decision process (MDP), because many reinforcement learning algorithms for this context use dynamic programming techniques [22].

1.8 Use of Machine Learning in Quality Testing

Figure 6 shows a typical working operation of an Artificial Neural Network system. Input data is processed and a hidden layer is created where deep learning takes place. The result is displayed as an output which may be in the form of command.

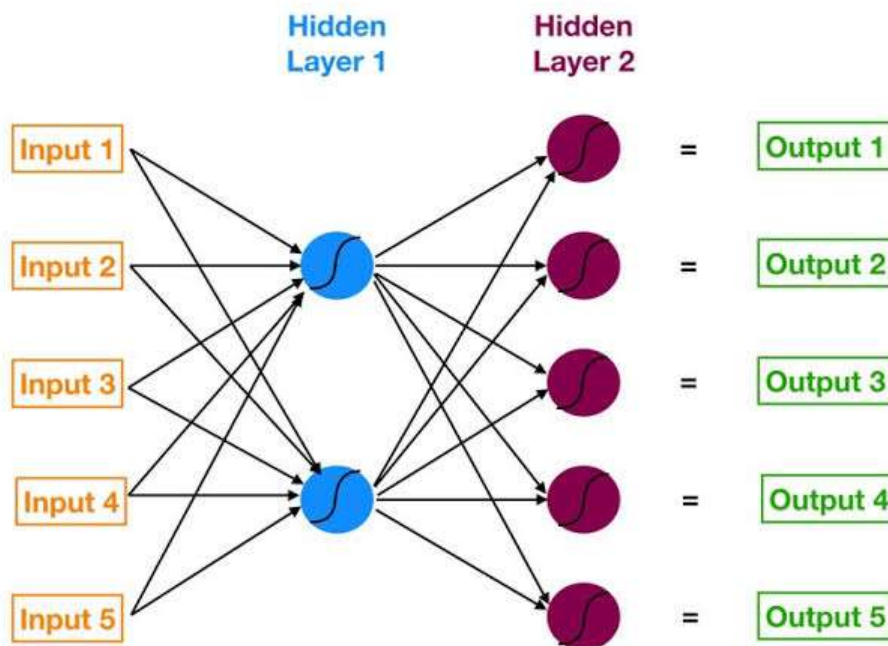


Figure 6: Artificial Neural Network Structure

Machine learning can use together with computer vision in quality assurance and control. Computer vision enables algorithms to be trained with pictures and videos with the help of computer processing unit (CPU) or the graphics processing unit (GPU). Upon completion of the learning process, the dataset is used in carrying out judgemental functions giving a true or false statement when the product meets the

required standard and when the standard falls below the acceptable standard.

This method has been used in various research works and in companies in detecting missing parts in their products and in control of machining parameters during machining operations.

However, for the purpose of this work, I will be using the supervised learning with computer vision

in quality assurance of surface finish during assembly operations.

Computer vision technology can be used in quality assurance of surface finish. This involves the use of camera in taking pictures of standard surface upon which every other surface is compared. The pictures captured are used in training with the algorithm. This makes use of supervised learning. Computer vision approach can be used to characterize surface texture using the concept that an image is presented as a two dimensional image intensity function characterized by two parameters which are amount of light incident on the surface and the amount of light reflected from the surface [23]. The amount of light incident on the surface depends on illumination whereas that reflected from objects is a function of surface irregularities and texture [23].

However, according to [23] machine learning can be carried out to model the relationship between vision approaches for surface roughness (Ra) values.

Computer vision plays a very important role in manufacturing automation. Computer vision technology is an artificial intelligence technology which allows the computer or Machine to learn and retain keys features in image which can then be used in imposing checks against quality. Computer vision is heavily employed in industries in quality assurance and control. Computer vision does this by interpreting the three dimensional details of the object from the two dimensional images [23]

Previous researchers have done a lot of work on computer vision [24], evaluated the roughness of machined surfaces by regression analysis and using machine vision. They had achieved this by magnifying the images using cubic convolution interpolation technique and through the use of Genetic Algorithm (Ga) in correlating this with the surface roughness[25].

Wong and Li (1999) used the combined effect of interference and light scattering to measure the roughness of a surface moving at a speed of up to 3.7 m/s in a cylindrical grinding process. Computer vision has been employed in detection of wears and cracks in tools and workpiece and tool control.

Computer vision has been employed in tool setting systems in CNC machine.

Tool setting is one of the important parts of CNC machine and it determines how effective and efficient the machining work will be accomplished. Computer Numerical Control machines is a method for automating control of machine tools through the use of software embedded in a microcomputer attached to the tool[26].

However, CNC machine work according to the principle of 3-axis motion control process. The CNC machines require that the X, Y and Z-axis are positioned accurately along the length of travel. Furthermore, the positioning may be done linearly or using rotary approach which allows the tool to move around a circular path. Tool control involve the use of part program instructions in controlling the machine tool motions, which is done through the computer interface or servo. However, CNC requires motor drive to control both the position and the velocity of the machine axes [27]. Also each axis is driven separately which must follow the command signal generated by the numerical control[27].

According to[28], a servo consists of several key components, including:

- (i) **Servo Motor:** A servo may be a rotary actuator or linear actuator which allows for precise control of angular or position, velocity and acceleration.
- (ii) **It Servo Drive:** It controls the Servo motor
- (iii) **Encoder:** A device that provides feedback to the servo drive.

- (iv) **Controller:** Control of servo drive to ensure the right amount of electrical power is delivered to the motor to perform the desired operation. A servo drive can be activated using the open-loop system or the closed-loop system. However, the primary characteristics of the open loop system is that there is no feedback system to check whether the desired position and velocity has been activated while a Closed Loop CNC system has a feedback Sub-system to monitor the actual output and correct the discrepancy from the programmed input[27].

A servo motor also called axis or torque motor uses closed loop Communication to achieve the needed accuracy and also for speed control. However, traditionally, tool position measurement and its verification were done using linear encoders, laser interferometers, actuators coordinate measuring machine (CMM), Atomic force microscope (AFM), Scanning Electron Microscope (SEM) [29].

Linear Encoders are sensor which are available as incremental or absolute reader and encompasses various detection techniques, namely, Mechanical, Optical, Magnetic and Capacitive types[29].

Linear Interferometer is an instrument used for most precise distance measurement using optical interference fringes [30]. However, according to [29], the advancement in technology in the field of micro and nanotechnology opens up new applications in assembling and manipulating components; hence, verification of motion in micro/nano range becomes as important as its activation and measurement.

However, at present the technologies of computer Vision have become a key part in next-generation intelligence vision CNC machines with the advantages of high precision, high efficiency, non-contact and intelligence[3] At present, various types of auto checking instruments for tool setting with high accuracy have been widely applied to CNC machine tools[31].

According to Liu, four types of automatic tool setting instruments are available, namely; plug and pull arms, pull down arms, automatic tool arms and automatic contact [32].

According to [3], the tool setting probe must be configured separately, and with the difficulties in installation process, the tool setting instrument is costly and the improvement degree of tool setting efficiency is limited.

The process of tool location is achieved by tool setting, that is accurately locating the cutter position point to the position of the tool setting point[33]. The cutter position point is the datum point to determine the position of the cutter[3]

Furthermore, considering lathe machine, the lathe tool cutter position point is the tip, the drill cutter position point is the drill point, the flat-end milling cutter position point is the centre of end surface, and the ball-end milling cutter position point is a sphere [3]. However, tool setting point refers to the starting point of the cutter relative to the workpiece machining movement [3].

However, according to [3], the tool setting point is selected as a design of the workforce. For a square workpiece, the intersection of the right end face of the workpiece and the centre line is usually selected as the tool setting point in the CNC lathe, whereas in CNC milling, the intersection point of the two vertical sides of the workpiece is taken as the tool setting point [3]. Also, considering a round workpiece, the centre is often selected as the tool point.

From the foregoing, [3] sums up the two key coordinate system for CNC matching and tool setting as the machine tool coordinate system (O-XYZ) and workpiece coordinate system (programming coordinate system, O-XYZ)

However, considering computer vision technology, the first stage involves image measuring and camera calibration. In order to have effective calibration system, parameters such as cutter displacement coordinate and mark point coordinate for calibration are obtained from position feedback of the numerical control system[3].

Furthermore, the technology involves use of camera, lens, boom stand, personal computer and two motion cards. The camera is used in image capturing. The image is converted to digital image. An algorithm programmed using MATLAB is used for processing the image. The camera is placed such that it can be moved steadily along the X and Y direction and the movement along the Z-axis adjusts the focus of the image with the help of the rack and pinion arrangement at the mounting plate [29]. However, the light projected onto the tool is captured through the lens by the sensors of CCD, which translate it into electrical signals according to the intensity[29]. These signals are processed and converted to digital image and thereafter sent to Computer processing unit.

Furthermore, the motion control mechanism is incorporated into the system to perform the motion and also compensate for positional difference of the tool as calculated by the algorithm developed using MATLAB software[29]. The system consists of an ultra-high resolution micro translation stage, a nano cube XYZ Piezo stage, a capacitive and strain gauge (SGS) position sensor, a data acquisition interface and a control PC.

According to [29], the following deductions could be obtained from the images:

- (i) Pixel Value: real world dimensions (millimetres or microns) of the images are extracted from the images.
- (ii) Tool positioning: images of both the reference (initial position) and traced positions (shifted positions) of tools were captured using the camera. An algorithm is applied to determine the horizontal and vertical distance as pixel dimensions traversed by the tool.
- (iii) Graphical User Interface (GUI): The GUI of the system is built in MATLAB. The developed GUI shows processes like calibration value, thresholding, feedback system and all the results.

The result obtained is subjected to statistical analysis. Tools like standard deviation are used to obtain the information of the data set from the mean value.

3.0 MATERIALS AND METHODS

3.1 Materials

Materials used in this research work were camera, form or standard machined surfaces and bad surfaces, a CPU and an algorithm.

The camera was used in image capturing. The computer processing unit, was used in processing the dataset.

3.2 Experimental Process

Convolution Neural Network process involve training an algorithm with a dataset which may be pictures and allowing the system to use the trained dataset in detecting when the quality has gone below the expected standard.

However, a camera was used in taking pictures, as many as possible. This pictures were used in training with the algorithm in order to allow the system to learn the surface and the features in the surface.

The images were trained with the algorithm. The training process took two months. This was due to the number of images trained, hence the length in time.

The system was also tested and the accuracy, losses and the mean error were evaluated. The system was able to draw up correlation between the trained dataset and any picture presented with and hence make judgement on a true or false basis.

However, this was done by using Convolution Neural Network (CNN) to detect metal surface in order to classify defects on metal surfaces. To do this, a dataset of 1800 images of metal surfaces was obtained. The defects were classified into 6 possible defects, with 300 images of metal surfaces for each defect.

- (i) 1620 images in the training set (90%)
- (ii) 180 images in the test set (10%)

3.3 Convolution Neural Network Architecture

Convolution Neural Network is a branch of deep learning and a class of Artificial Neural Network which is particularly helpful in solving computer vision based problems. Convolution neural network (CNN) is particularly powerful and efficient in problems involving image recognition, classification and processing of features from pixel of images – it uses mathematical operation called convolution - hence its choice. Convolution neural network is made up of neurons with learnable weights and biases. The neurons receives input data which is processed as weighted sum and then passed through activation function to give an output.

Images contains pixel data, which was extracted and represented in numerical form. This formed the main features that was used in processing with the CNN. Convolution neural network is made of layers. The input layer is where the image data is inputted. The information contained in the dataset is then processed by a series of hidden layers. These layers are the convolution layer, the pooling layer, and the Full connected (Fully connected Layer), and the output layer. Thus, the neurons – which operates in similar ways as the biological cells – learns how to convert the input data, which is the features found in the dataset to output signals. The architecture is made up of operations; the convolution operation, pooling operations, after which we have the fully connected layers.

However, the system was programed to perform calculations on the architecture of the model from the features extracted from the dataset. This calculations are done with the help of

the algorithm. This calculations are done on layer basis as shown below;

(i)Input Layer: input layer was received in this layer. It represented the pixel matrix of the image.

The input shape of the image is (200, 200, 3), where 200 represents the height and width of the image, and 3 represents the number of color channels (RGB). Therefore, the total number of input neurons in the input layer is:

$$\text{Input neurons} = \text{height} * \text{width} * \text{channels} = 200 * 200 * 3 = 120,000$$

(ii)Convolution Layer:

This is where the output that are connected to input dataset are calculated. This involve calculating the dot product between input weights and the receptive field that connects them in input volume.

The convolution layer is made up of filters. It should be noted that each convolution filter represents the features - which are the pixel information of the dataset - which the algorithm learns, in order to perform calculations. The first convolutional layer has 32 filters. The kernel size is (5, 5). Since the padding is set to "same," the output spatial shape will be the same as the input spatial shape. The stride is 1, which means the filters move one pixel at a time. The number of parameters in each filter is calculated as follows:

$$\begin{aligned} \text{Number of parameters per filter} &= (\text{kernel_height} * \\ &\text{kernel_width} * \text{input_channels} + 1) * \text{output_channels} \\ &= (5 * 5 * 3 + 1) * 32 \\ &= 2432 \end{aligned}$$

Therefore, the total number of parameters in the first convolutional layer is $32 * 2432 = 77,824$.

(iii) Pooling Layer:

Pooling layer is in between the convolution layer and the fully connected layer. The maximum pooling is a technique of sub-sampling which allows for generalization of data. Maximum (Max) pooling enables input to be obtained by reducing its dimensions , which in return helps in reducing overfitting. Overfitting, being a model error occurs when a function aligns too closely to a limited set of data, which becomes difficult for the model to generalize on new training set. A model is said to be overfitted when it performs well in training and poorly during test, which is due to its inability of the learn and memorize.

In maximum pooling, the maximum pixel values are selected here which represents the maximum value of the input data. The values are calculated and the result down sampled (reduces dimensionality of input data). Maximum pooling helps in reducing the number of parameters.The max pooling layer reduces the spatial dimensions of the feature maps by a factor of 2. The pool size is (2, 2), which means the maximum value in a 2x2 region is selected. Since the pooling layer doesn't introduce any additional parameters, the number of neurons remains the same.

(iv) Convolutional Layer and Pooling:

The second set of convolutional layers follows a similar pattern as the first. The second set has 64 filters, and each filter has a kernel size of (3, 3). The stride is 1, and the padding is "same." Therefore, the number of parameters in each filter is:

$$\begin{aligned} \text{Number of parameters per filter} &= (3 * 3 * 32 + 1) * 64 \\ &= 18,496 \end{aligned}$$

The total number of parameters in the second convolutional layer is $64 * 18,496 = 1,181,184$.

The second max pooling layer reduces the spatial dimensions by another factor of 2.

(v) Dense Layer:

After the convolutional and pooling layers, a dense layer with 256 neurons is added. The input to this dense layer is the output from the previous layer, which is a tensor of shape (25, 25, 128). The number of parameters in this dense layer is calculated as:

$$\begin{aligned} \text{Number of parameters} &= (\text{input shape} * 256) + 256 \\ &= (25 * 25 * 128 * 256) + 256 \\ &= 20,480,256 \end{aligned}$$

(vi) Flattening Layer:

The flattening layer converts the tensor from the previous layer, which has dimensions (25, 25, 128), into a 1D vector. The total number of neurons in the flattening layer is equal to the product of the dimensions:

$$\text{Neurons in the flattening layer} = 25 * 25 * 128 = 80,000$$

These calculations provide the specific details of the layer dimensions and parameters in the given model architecture.

3.4 Model Epoch

Epoch refers to the training the model received when the dataset was exposed to the algorithm. An Epoch consist of one complete cycle of dataset training, hence, the total number of Epoch reflects the number of times the dataset was trained with the algorithm. Hence, for accuracy sake, the training period was carried out for 150 times. The essence for the repetition was to allow for attainment of a smaller value of mean error. This also allows the system opportunity to learn the input data and also perform the necessary calculations on it.

Moreso, as said earlier, the work was partitioned into batches, called iteration – number of batches needed to complete one epoch. The batches here is the number of training samples used in one iteration. However, there were 24 batches

3.5 Setting up the Tensor Flow

Tensorflow is a platform used in machine learning. This is a multidimensional array used in storing up data. The dimensions are called features which can be represented in a 3-dimensional tensor - in X, Y, and Z planes - tensors are deep data. Tensorflow high level API are used based on Keras API standard. This enables data training a rapid prototyping. However, a Kera – which is a high level neural network library – allows for creation of deep learning models, upon which the different layers were generated.

Furthermore, the study used the Tensorflow platform with Keras in model development. The steps undertaken in setting up the system involved installation of Python application on the Personal Computer. The system is thereafter launched by importing Tensorflow and following each step presented below:

- (i) Import Tensorflow
- (ii) Download and prepare the Dataset
- (iii) Verification of Data
- (iv) Creation of convolutional base
- (v) Addition of dense layer
- (vi) Compilation and training of model
- (vii) Evaluation of model.

3.6 Data Training

The dataset obtained was subjected to training with the algorithm using convolution neural network, which helped in data classification.

3.6.1 Labeling of Samples

The samples were grouped into six major groups, depending on the defects. This dataset formed the basis upon which bad surfaces are defined and in so doing the system gets this knowledge and allows it to recognize such surfaces when seen. This was obtained after the dataset comprising of 1800 images were trained with the algorithm.

3.6.2 Algorithm Formation

The images were trained with the algorithm in other to learn specific steps that must be followed to achieve results.

The algorithm was written in Python programming language, while the Convolution Neural Network (CNN) was used in classifying and training the images. Convolution Neural Network is a branch of Artificial Intelligence deep learning which has applications in image recognition. This involved processing of the Pixel data.

Data training here involved training the images with the algorithm, which allows the pixel values of the images to be obtained and the weighted value of it calculated. The neurons learn the character of the dataset which allows it to gain knowledge and recognition of bad surfaces. The algorithm is found in the Appendices. The steps followed are as presented below.

- (i) Import Dependences: .
- (ii) Loading the Dataset: The path is set to training and testing dataset. This was achieved using the algorithm
- (iii) Find the distribution of each of the defect: The distribution of the 6 classes of defects was found using the algorithm
- (iv) Show Random Image from Training Dataset: The program is written to allow for randomization of images in the dataset. This step allows for increase generalization of the algorithm to the new environment. In this step dataset was assigned to

groups at random in order to avoid bias and undue influence on result.

- (v) **Data Preparation and Augmentation:** Data augmentation is applied in order to prevent overfitting. The performance and outcomes of machine learning models is improved by forming new and different examples to train datasets. This is especially helpful since the dataset is small. Augmenting the images increases the dataset as well as exposing the model to various aspects of the data. This is achieved by using geometric transformations such as flipping, rotation, translation, cropping, scaling, and color space transformations such as color casting, varying brightness, and noise injection. The program for this is presented in Appendix 5.

Total Augmented Images = Batch Size*Number of Epoch = 24*150 = 3600.

- (vi) **Creating a Tensor Flow dataset from the images:** The system was programmed to allow for tensor flow dataset to be created from the images. That can be done using the `image dataset from directory`. The classes will be reference from the folder structure. To generate the dataset, we need to define the following parameters:
1. The path to the dataset
 2. An optional seed for shuffling and transformations
 3. The `target_size` is the size the images will be resized to after being loaded from the disk
 4. Since this is a category classification problem the `class_mode` is categorical
 5. Batch_size=10` means that the images will be loaded in batches of 10

- (vii) **Callback:** A callback of object was setup to perform actions at various stages of training, at start or end of an epoch, before and after a single batch. Callback was used to validate or correct certain behaviours. It also serves the purpose of allowing the system performance to be assessed and also in stopping the training once the accuracy reaches the threshold. The application of callback in this work was to ensure that an accuracy of 98% was attained during training and also create measures of correcting behaviours that were not appropriate during training. Callback serves the purpose of defining what happens during training.
- (viii) **Save the Best Model Automatically:** The path to automatically save the best model or model weights during training is set. Keras Model Checkpoint

callback is used. The callback then saves the best model after each epoch.

- (ix) **Setup of Convolutional Layers:** The 2D Convolution Neural Network was Built. Convolutional neural network (CNN) model was created which was used to classify the images.

- (ix) **Compiling the Model:**

The steps were:

Step 1: Set the optimizer used by the model: Adam optimizer was used in this instance, as specified in the Keras documentation. The Adam optimizer (Adaptive Moment Estimation) is an improved version of gradient descent. Interestingly, the Adam algorithm does not use a single global learning rate Alpha. It uses a different learning rate for every single parameter of our model. The intuition behind the Adam algorithm is that if the coefficients (weights and bias) keep moving in roughly the same direction, Adam will increase the learning rate for that parameter. In other words, it makes the process faster in that direction.

Step 2: Specify the loss function of the model: Since the dataset was a Multi-class Classification “categorical_crossentropy” was used.

Step 3: Specify metric to evaluate model performance: Categorical Accuracy metric, as stated in the Keras documentation was used for categorical data.

- (xi) **Training the Model:** The next step is to train the model. The mode trains 150 Epochs.

This involved feeding the neural network with the labeled dataset. In this case, `y` is not passed in. That was taken care of by the function used to generate the training set. Passing the validation data is critical so that the loss and accuracy can be accessed later and plotted. The previously defined callbacks were used.

- (xii) **Model Performance:** Using the history object, the training losses and accuracies was obtained from using the algorithm

- (xiii) **Check the performance of the model on the test dataset:** The performance of the model on the test dataset was found using the program written.

- (xiv) **Load Trained Model:** In order not to retrain the model, we need to read it from the save directory

- (xv) **To create model instance and predict new image:** This allows for new models (test samples) to be uploaded.

- (xvi) **Function to Predict New Image:** This is where the new model that was uploaded earlier is predicted.

3.7 Testing the Model with the Dataset

The following steps are taken when testing the model with the Dataset.

1. The dataset is uploaded to Google drive.

2. The program is made to run using a Personal Computer.
3. The test samples are snapped and the images uploaded to Google drive.
4. The program under predict image is made to run using the lead cursor.
5. The sample is then predicted, whether it conforms to the standard or not.

3.8 Model Efficiency

The efficiency of the model is measured in terms of the accuracy and error. Accuracy measures how well a model performs across all classes. It is a ratio of number of correct predictions made by the model to the total number of predictions made. The accuracy of the system is classified into Training accuracy and validation accuracy. Accuracy was calculated by dividing the number of correct predictions by the total number of predictions. The metric was expressed as a probability (obtained directly from the model), and as percentage – obtained by multiplying the probability value obtained from the system by 100 percent. This is shown in Appendix 15.

Training accuracy measures the accuracy of the model on the dataset it was trained on. It is a measure of how successful the model was during training. Training accuracy shows how well the model learnt the labels on the training dataset, with the associated textural features.

However, in order to ensure robustness in the system, the model was validated (tested) after training. Validation Accuracy probes the system’s ability to learn the features in the training dataset and draw up similarities when tested with a new model (dataset). This shows how accurate the model will be on new data (data not used during training). It evaluates the efficiency of the system, as it provides a picture of both the system’s quality and the products quality during assembly. This shows how well the model can predict the product’s quality from the quality specification of a product stipulated during product design.

The system error was also found. Error occurs due to misclassification of data. Error occur through the following ways;

- (i) **Mislabeled Data:** this error occurs when the dataset are wrongly labeled. Labeling of dataset enables the system to understand, learn and memorize the textural features in the dataset. When this dataset are not properly labeled, it sets the system on the path of confusion as the system may not be able to understand how to appropriate the features in the dataset. This error was avoided, as the dataset of the different classes were well labeled.
- (ii) **Hazy line of Demarcation:** this occurs when the dataset are not properly classified. This results in inability of the system in distinguishing the

different classes of data. The defects were well classified, hence, this error was avoided.

- (iii) **Overfitting and Underfitting of Dimensions:** overfitting occurs when the model performs well with training dataset, but could not replicate same when tested with a different dataset. However, underfitting occurs when a model is unable to represent the relationship between input and output parameters accurately. On the whole, errors due to overfitting or underfitting occur due to inability of the model to learn the dimensions from the available data. However, there was no overfitting or underfitting.

The training and validation error of the model was found. Training errors are errors measured in the training sample.

Training and Validation Errors in the model was calculated as Losses in the model.

The training loss of the model was found by taking sum of the errors in each Epoch in the training set. This loss was also plotted graphically as training loss against the Epoch. This enabled assessment of the performance of the model – in term of how well the model fits the training data.

Validation Loss is a metric that enabled the assessment of the performance of the model on the validation dataset. The validation loss was measured after each epoch and also plotted as a graph of Validation Loss against Epoch. This metric enable us to know whether there was an overfitting in the system – enabled system adjustment. The values generated from each Epoch enabled the model performance to be validated.

3.8.1 Mean Error

Mean error is calculated from the Mean Absolute Error (MAE). Mean Error is the average of all the individual errors. Mean absolute error refers to the mean of the absolute difference between the predicted value and the true value of the observation.

However, Mean Error is calculated by taking the mean of the absolute difference the true labels and the predicted labels. This enables understanding of the model performance over the whole dataset. Mean error was found using the algorithm in Appendix 15.

Mean Absolute Error was calculated using the Numpy library thus;

True labels and Predicted labels are picked as arrays

```
y_true_labels = np.array([1, 2, 3, 4, 5])
```

```
y_pred_labels = np.array([2, 3, 4, 5, 6])
```

```
# Calculate the mean absolute error
```

```
mae = np.mean(np.abs(y_true_labels - y_pred_labels))
```

```
print("Mean Absolute Error:", mae).
```

However, the Mean Error was then found thus,

$$\text{Mean Error} = \text{np.mean}(\text{np.abs}(y_true_labels - y_pred_labels))$$

3.9 Dataset Presentation

The images of some the dataset as presented below. The accuracy of the system is classified into training accuracy and validation accuracy. The images were classified into six different classes based on the defects.

4.0 RESULTS AND DISCUSSION

4.1 Results

From the steps highlighted in Chapter Three, the image of the samples were trained with the algorithm and the results obtained are herein discussed.

Six datasets comprising of 1800 images were subjected to training as captured in chapter Three. This resulted in neurons gaining knowledge and hence their conformance with the algorithm, which allows the system to carryout prediction of good and bad surfaces. The results from the training and testing are presented Figure 7 and Figure 8.

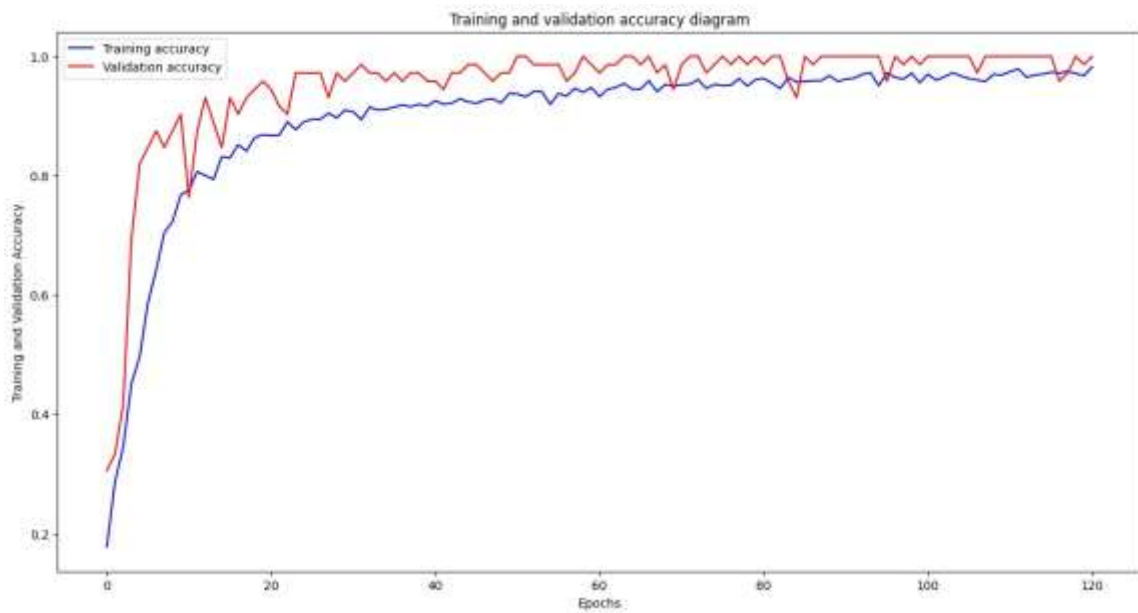


Figure 7: Graph showing Training and Validation Accuracy against Epoch

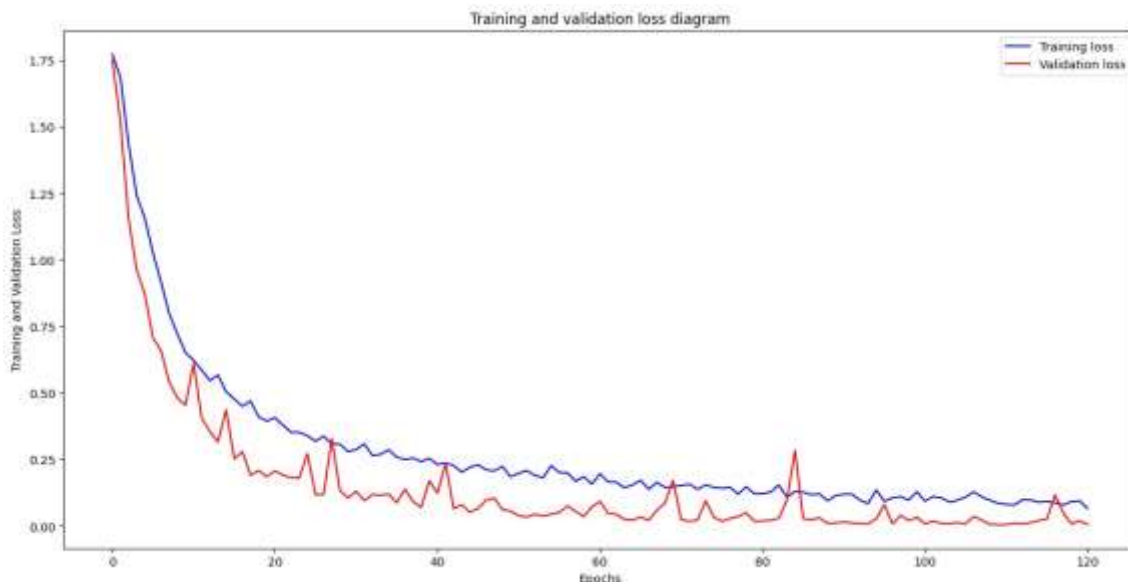


Figure 8: Graph showing Training and Validation Loss against Epoch

Table 5 shows the performance of the system during training for 150 times and Table 5 the summary of model architecture.

Table 5: Performance of the System during Training for 150 Layers

Epoch	Accuracy	Loss	Validation Accuracy	Validation Loss	Remark on Validation Accuracy
1/150	0.1603	1.7797	0.1667	1.7713	Improved
2/150	0.2119	1.7457	0.3056	1.6982	Improved
3/150	0.3139	1.5992	0.3889	1.3885	Improved
4/150	0.3824	1.3815	0.6111	1.1440	Improved
5/150	0.4568	1.2480	0.6528	1.0781	Improved
6/150	0.5420	1.1024	0.6667	0.9732	Improved
7/150	0.5714	1.0227	0.7500	0.7730	Improved
8/150	0.6327	0.9455	0.8056	0.6975	Improved
9/150	0.6627	0.8606	0.8333	0.5891	Improved
10/150	0.6807	0.8279	0.8194	0.5571	No improvement from 0.8333
11/150	0.7197	0.7537	0.83333	0.5422	No improvement from 0.8333
12/150	0.7407	0.7111	0.8611	0.5101	Improved
13/150	0.7491	0.6814	0.7639	0.5678	No improvement from 0.8611
14/150	0.7695	0.6344	0.8889	0.3593	Improved
15/150	0.7785	0.5976	0.8750	0.4560	No improvement from 0.8889
16/150	0.8049	0.5711	0.7778	0.5837	No improvement from 0.8889
17/150	0.8109	0.5418	0.9028	0.3360	Improved
18/150	0.8115	0.5427	0.9306	0.2724	Improved
19/150	0.8427	0.4764	0.9306	0.2691	No improvement from 0.93056
20/150	0.8403	0.4612	0.9306	0.2738	No improvement from 0.93056
21/150	0.8427	0.4478	0.9028	0.3022	No improvement from 0.93056
22/150	0.8325	0.4715	0.9444	0.2247	Improved
23/150	0.8505	0.4203	0.9583	0.1903	Improved
24/150	0.8391	0.4673	0.8750	0.3550	No improvement from 0.9583
25/150	0.8691	0.3997	0.9167	0.2524	No improvement from 0.9583
26/150	0.8697	0.3840	0.9028	0.3192	No improvement from 0.9583
27/150	0.8764	0.3781	0.9444	0.1779	No improvement from 0.9583
28/150	0.8902	0.3372	0.9167	0.1944	No improvement from 0.9583
29/150	0.8836	0.3382	0.9306	0.1613	No improvement from 0.9583
30/150	0.8673	0.3686	0.9167	0.2057	No improvement from 0.9583
31/150	0.8547	0.4029	0.9444	0.1619	No improvement from 0.9583
32/150	0.8866	0.3425	0.9444	0.1428	No improvement from 0.9583
33/150	0.8908	0.3410	0.9306	0.2084	No improvement from 0.9583
34/150	0.8884	0.3323	0.9306	0.1607	No improvement from 0.9583
35/150	0.9028	0.2854	0.9306	0.1737	No improvement from 0.9583
36/150	0.8992	0.2958	0.9028	0.2488	No improvement from 0.9583
37/150	0.8998	0.3020	0.9306	0.1696	No improvement from 0.9583
38/150	0.9064	0.2789	0.9583	0.1535	No improvement from 0.9583
39/150	0.9034	0.2840	0.9583	0.1278	No improvement from 0.9583
40/150	0.9076	0.2825	0.9444	0.1141	No improvement from 0.9583
41/150	0.8980	0.2959	0.9306	0.1510	No improvement from 0.9583
42/150	0.9118	0.2582	0.9583	0.0974	No improvement from 0.9583
43/150	0.9004	0.2784	0.9306	0.1259	No improvement from 0.9583
44/150	0.9154	0.2461	0.9444	0.1954	No improvement from 0.9583
45/150	0.9112	0.2545	0.9444	0.1336	No improvement from 0.9583
46/150	0.9202	0.2594	0.9583	0.1410	No improvement from 0.9583
47/150	0.9112	0.2466	0.9583	0.0961	No improvement from 0.9583
48/150	0.9160	0.2341	0.9444	0.1977	No improvement from 0.9583
49/150	0.9250	0.2422	0.9306	0.2139	No improvement from 0.9583

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50/150	0.9214	0.2248	0.9722	0.0894	improved
140/150	0.9712	0.0873	1.0000	0.0085	improved
141/150	0.9730	0.0844	1.0000	0.0152	improved
142/150	0.9784	0.0729	0.9306	0.3097	No improvement from 1.000
143/150	0.9790	0.0725	1.0000	0.0080	improved
144/150	0.9706	0.0853	0.9722	0.1111	No improvement from 1.000
145/150	0.9694	0.0958	1.0000	0.0071	improved
146/150	0.9610	0.1065	0.9722	0.1268	No improvement from 1.000
147/150	0.9778	0.0692	0.9583	0.1252	No improvement from 0.9722
148/150	0.9574	0.1291	0.9306	0.1992	improvement
149/150	0.9760	0.0827	0.9861	0.0412	Improved
150/150	0.9670	0.0932	0.9861	0.0502	unchanged

Table 6: Summary of Model Architecture

Layer (type)	Output Shape	Param #
=====		
conv2d (Conv2D)	(None, 200, 200, 32)	2432
conv2d_1 (Conv2D)	(None, 200, 200, 32)	9248
max_pooling2d (MaxPooling2D)	(None, 100, 100, 32)	0
conv2d_2 (Conv2D)	(None, 100, 100, 64)	18496
conv2d_3 (Conv2D)	(None, 100, 100, 64)	36928
max_pooling2d_1 (MaxPooling 2D)	(None, 50, 50, 64)	0
conv2d_4 (Conv2D)	(None, 50, 50, 128)	73856
conv2d_5 (Conv2D)	(None, 50, 50, 128)	147584
max_pooling2d_2 (MaxPooling 2D)	(None, 25, 25, 128)	0
dropout (Dropout)	(None, 25, 25, 128)	0
flatten (Flatten)	(None, 80000)	0
dense (Dense)	(None, 256)	20480256
dropout_1 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32896
dropout_2 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 6)	774

Total params: 20,802,470
 Trainable params: 20,802,470
 Non-trainable params: 0

4.2 Discussion

The results are presented in Table 5 - showing the accuracy and losses during training and validation - while Table 2 shows the architecture of the model. However, Figure 7 and

Figure 8 shows accuracy and loss plots during training and validation.

Table 5 was extracted from results generated from computer programme.

However, the different layers making up the model is shown in Table 6. These layers are shown as input layer, the hidden layers and the output layers. Also, the parameters (params), which are the values of the learnable components in a model. The input layers have no learnable parameter as it serves the purpose of providing the input image shape. The Convolution (CONV) layers is where learning took place. It is the core building block, hence, computations occurred here. However, in Max pooling, maximum pixel values from each pool is computed here.

4.2.1 Training and Validation Accuracy

The performance of the system during training and validation are herein discussed. The training and validation accuracy shown in Table 5 can be expressed as a percentage by multiplying each of the values by 100.

(i) Training Accuracy

The data obtained after training and validation were plotted graphically as presented in Figure 1. The graph shows the overall performance of each Epoch during the training process. Accuracy shows how well each Epoch performed in training. Typically, Accuracy can also be expressed as a percentage. Accuracy allows the training phase to be monitored, so as to know the overall performance of the model.

However, from the plot in Figure 1, it can be seen that there is a gradual increase in the training accuracy of the model. Though the accuracy of the first Epoch was poor – giving a value of 0.1603 over a scale of 1.0, which conforms to Epoch 1/150 - other values of accuracy increases progressively over the training period, with Epoch 2/150, 3/150, 4/150 and 5/150 recording accuracies of 0.2119, 0.3139, 0.3824, respectively over a scale of 1.0.

The trend is sustained up to Epoch 23/150, thus recording an accuracy of 0.8505. However, there is a decrease in the value of accuracy in Epoch 24/150, which recorded a value of 0.8391. Epoch 25/150 records an increase, which is sustained up to Epoch 28/150 as seen in Table 5 and Figure 7.

Additionally, some of the high values obtained were 0.9712 and 0.9670 by Epoch 140/150 and Epoch 150/150 respectively. However, Epoch 149/150 recorded 0.9778.

From the plot, we can deduced that the accuracy of the model was fairly progressive, thus maintaining an almost smooth trend.

The discussion presented above has proven that the predictions obtained from the model were correct, hence the high accuracy obtained.

(ii) Validation Accuracy

The validation accuracy is represented in Figure 1, and is plotted on the same scale and axis as the training accuracy. The validation accuracy of Epoch 1/150 was 0.1167. This value increased progressively over the validation period, and

thus forming a trend up to Epoch 9/150, which recorded a value of 0.8333 over a scale of 1.00.

Furthermore, subsequent iterations above Epoch 9/150 recorded slight drops. Epoch 10/150, 11/150, 12/150 and 13/150 recorded 0.8194, 0.8333, 0.8611, and 0.7639, respectively. However, some of the high values were 0.9306 recorded in Epochs 33/150, 34/150, 35/150, and 37/150; 0.9444 obtained in Epochs 27/150, 44/150, 45/150, 48/150 and 0.9583 recorded in Epochs 38/150, 39/150, and 42/150 as seen Figure 1 and Table 5.

However, 1.000 validation accuracy was achieved in Epochs 141/150 and 143/150, thus corresponding to 100 percent accuracy.

However, the drops in the validation accuracy in some Epochs is due to the fact that the data training were done in batches.

4.2.2 Training and Validation Loss

Training and validation loss are presented in Table 5 and Figure 8. The training and validation loss is plotted as Loss against Epoch.

(i) Training Loss

The training loss in Epoch 1/150 was 1.7797 and decreased down the column as seen in Table 4.1, recording values as low as 0.0852 in Epoch 120/150 in Appendix 16, hence, gradually approaching 0 value. This further buttresses the effectiveness of the model.

The extrapolations from the low training loss values is that the predictions were correct.

From Table 5, it can be seen that the losses reduces continuously till it crashes to 0.0852. This means that there was a continuous system adjustment and improvement as more Epochs were being trained. The implication of this low values of training loss is that the model performed well during training and does not need further training and augmentation to improve the parameters. It also implies a high accuracy of the training process. It means that there are fewer errors in the model.

However, the training Loss graph gives a fairly smooth curve which follows a trend.

(ii) Validation Loss

Validation loss follows the same trend as the training loss. Epoch 1/150 recorded an all-time high of 1.7713 which marks the beginning of the validation period.

This value decreases down the column as seen in Table 5, with the three successive values recording 1.6982, 1.3885 and 1.1440. Epoch 50/150 records 0.0894.

The lowest values recorded were; 0.0193 in Epoch 94/150; 0.0170 in Epoch 95/150; and 0.0111 Epoch 129/150. However, the low values of validation loss implies that the model was able to learn, understand and memorize the features in the training dataset and also made accurate predictions on new sets of data - that the new sets will be predicted more accurately. Also, the fact that the validation

loss is lower than the training loss implies that there was no overfitting.

4.2.3 Model Architecture

The summary of model architecture is presented in Table 5. The Model architecture is the underlying structure upon which the algorithm executes the task. The input neuron was 120000, which was obtained as explained in chapter 3. This means that the first layer of the CNN will be 120000. This equal to the total number of input variables in the data processed.

The Model Architecture consists of 6 CONV 2D (Convolution) layers, 3 Pooling layers, 3 Dense layers and two dropout layer.

The Dense layer is a fully connected layer. In Dense layer, every neuron is connected to the neurons in the previous (preceding) layer. In Dense layer, the dense layer neurons receives output from the previous layer. This neurons then performs a matrix – vector multiplication operation - where the row vector of the output from previous layer equals to the column vector of the dense layer.

Dropout layers helped in generalization of data in order to avoid overfitting. Dropout layers nullifies the contribution of some neurons with unwanted data called noise.

Flattening layer was used to convert the multidimensional arrays into one dimensional arrays.

However, in the first layer of convolution layer, the number of filters were 32 and the kernel size of (5,5), which gave 2432 parameters per filter and a total of 77842 parameters for the layer. The second layer of the convolution had 64 filters, with a kernel size of (3,3), which gave 18,496 per filter and a total of 1,181,184 parameters for the layer.

Considering the pooling layer, the pooling had three layers. The pooling layer down sampled the input data along its spatial dimensions – the heights and widths. However, in pooling layer, had a pool size of (2,2). The dimensions of the output shape from the convolution layer was reduced, by

dividing the height and width by 2. The output shape obtained from the input data was (200, 200, 32) which means that the height, width and the filter values were 200, 200, 32 respectively. However, the pooling layer reduced the height and width to 100 while the filter increased to 64 (100, 100, 64). This became an input data for the second layer of the convolution.

However, the second layer of pooling further reduced the output shape to (50, 50,128), which was obtained by dividing the height and the width by 2, while the filter was multiplied by 2. There is a third layer of pooling which gave an output size of (25, 25, 128).

Furthermore, from Table 2, it can be seen that the total parameters equal to the trained parameters. This means that all the learnable neurons were trained.

The dataset used in validation are presented below.

4.2.4 Mean Error

The mean error of the model was found which enables the overall performance of the system to be found. The mean error of the system was 2.11.

4.3 Validation of Results

The results of the study was validated by comparing it with previous work of Convolution Neural Network, on a Comparative Study of Different Deep Learning Model for Recognition of Handwriting Digits by Pronab *etal* (2021) and Krzysztof (2015) on Testing the Accuracy of surface roughness Measurement using Portable profilometer. Other works were also considered as presented in Table 7.

It can be seen from Table 3 that, the contact process measurement had accuracy of 94.04%, while CNN model by Pronab *etal* had an accuracy of 99.7%. However, similar work was done by Chen *etal* using Artificial Neural Network, giving an accuracy of 96.8%. However, the model developed in this study has an accuracy of 98%.

Table 7: Comparison between our Studies and Previous Studies

References	Approach	Feature	Accuracy
Pronab <i>et al.</i>	CNN	Pixel Based	99.7%
Krzysztof stepien	Contact Process	Rsm	94.04%
Chen <i>et al.</i>	ANN	Pixel Based	96.8%
Proposed Model	CNN	Pixel Based	98%

Also, another parameter considered when evaluating the performance of a system in Convolution Neural Network is the deviation of the training accuracy from the validation accuracy. Studies have proven that large differences between the values of training accuracy and validation means that there was overfitting which is not good for the system, while small values mean that overfitting was avoided. The values presented in Table 5 which was further plotted as graph in

Figure 1 shows this relationship. From the values in Table 1, it can be seen that the deviation between the training accuracies and validation accuracies is small, which is further shown in the plot in Figure 8, the deduction from this is that, there was no overfitting, hence the narrow gap between this two metric values.

5.0 CONCLUSION

From the results of the research presented in Table 3, it is clear that Artificial Intelligence based method of surface assurance, is more efficient than the contact process – which involve use of profilometer. The accuracy obtained from this study was 98%, while the accuracy of contact process has approximately a 5% error as seen as seen in the 94.04% accuracy recorded. it could be seen that artificial intelligence is potent and capable of meeting the demands and solving the long term challenges in Quality Assurance and Quality control. The quality of the results of the research calls for its adoption and implementation in industries.

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