Tool Life Prediction in CNC machine using Machine learning and neural network based on machine vision

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Major Project Report

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(Computer aided Design/ Computer aided Manufacturing)

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May - 2021

Declaration

This is to certify that

1. The thesis comprises my original work towards the degree of Master of Technology in Mechanical Engineering (CAD/CAM) at Institute of Technology, Nirma University and has not been submitted elsewhere for Degree.
2. Due Acknowledgment has been made in the text to all other material used.

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Undertaking of originality of work

I, Pranavkumar Darji, Roll. No. 19MMCC18, give undertaking that the Minor Project entitled "Tool Life Prediction in CNC machine using Machine learning and neural network based on machine vision" submitted by me, towards the fulfillment of the requirements for the Subject Major Project in M.tech (CAD/CAM) of Institute of Technology, Nirma University, Ahmedabad, is the original work carried out by me and I give assurance that no attempt of plagiarism has been made. I understand that in the event of any similarity found subsequently with any published work or any dissertation work elsewhere it will result in severe disciplinary action.

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Certificate

This is to certify that the Major Project Report entitled "**Tool Life Prediction in CNC machine using Machine learning and neural network based on machine vision**" submitted by **Mr. Pranavkumar darji (Roll No. 19MMCC18),** towards the partial fulfillment of the requirements for the award of Degree of Master of Technology in Mechanical Engineering (Computer aided Design and manufacturing) of Nirma University is the record of work carried out by him under our supervision and guidance. The work submitted has in our opinion reached a level required for being accepted for examination. The results embodied in this major project work to the best of our knowledge have not been submitted to any other University or Institution for award of any degree or diploma.

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Approval Sheet

The Project entitled "**Tool Life Prediction in CNC machine using Machine learning and neural network based on machine vision**" by Pranavkumar Darji (19MMCC18) is approved for the thesis in Semester-III in Mechanical Engineering (CAD/CAM) of Nirma University, Ahmedabad

Examiners

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Date: ___________

Place: __________

Acknowledgment

"Our duty is to encourage everyone in his struggle to live up to his own highest idea, and strive at the same time to make the ideal as near as possible to the truth. "I would like to extend our heartily thanks with a deep sense of gratitude and respect to all those who provide us immense help and guidance during our project.

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Yours Sincerely,

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Abstract

Tool Conditioning Monitoring (TCM) is the one of the main part in the field of the machining. In various ways tool conditioning monitoring can be happen like manual way, Indirect way, and Direct way. By these ways of the TCM can find the Remaining useful tool life and tool wear. So, till this time in many industries there is use of the manual way of the tool life by using the microscope and calculation of the wear area or by using machining time guessing of the tool life. So due to that sometimes if there is mistake in the machining time tool can be break before that so it can cause the accident of the error in machined part. In this era many researchers have focused on the Indirect way due to it is very low-cost system, indirect way uses various effective factors like force, voltage etc. so depend on the sensor collected data it predicts the life if tool. But it has limitation of reduced error up to 7-10% based on literature. So, there is use of the Direct way which collects the data from the image of worn tool and based on that data it predicts the life of tool and it reduce the life prediction error up to 5-4%. And if there is use of the effective neural network it reduces the error more.

So, looking forward the 4th revolution era of industry, an attempt will make in this project to develop the tool life prediction system by using the machine vision system and Neural network. Various literature are studied to identify the various methods to collect the data from image by image processing techniques and use that data in neural network to predict the tool life and tool wear. There is use of the GUI to conduct this image processing, collection of data and neural network prediction. By using python programming language developed the GUI for the Image processing and using the Binary image extraction technique to collect the data from the image. There is use of the Sigmoid function ANN and ReLU function ANN for prediction of the tool life after collect the data from the experiment. In the experiment there is setup of Industrial camera system and illumination system in CNC to collect the image at prescribed time gapes.

Key words: - Machine Vision, Neural network, Tool life Prediction, Tool Conditioning Monitoring, Color cluster image processing.

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CHAPTER 1

Introduction

The introductory chapter offers an insight into the rationale of the subject of the study and incorporates several concepts that are relevant to it. The chapter also aims to take up this thesis work and the framework followed here to present the same, following a fundamental introduction into several aspects of AI, Tool wear, and maintenance.

1.1 Preliminary Remarks

In this era of the 20th century, there is the Growth of technology in every sector with the Automation of processes. The main industry is the Machining and production industry who is having high changes with this revolution of this change. As a result, it is not enough to increase productivity in modern manufacturing industries; it is also necessary to increase component or product quality in form of dimensional precision and Finishing of the surface by choosing the appropriate tool-workpiece, cutting standards, coating material, and inventory plan instruments for uninterrupted manufacturing.

In this era of automated machining, there is a need for CNC (Computer Numerical Control). These CNC machines allow programmability and high automation for the process of turning. There is one crucial aspect, however, which is still done by hand: The wear calculation of the cutting tool used in the turning process. There is no industry-wide adoption for automating the wear measurement process. Instead, wear calculation involves stopping the automatic spinning, removing the instrument, weighing the instrument, and placing the instrument in place back into the tool's holder. The time lost to calculate that the instrument would only last minutes in a typical turn and sometimes it breaks during the process too.

Tool condition monitoring is a significant component of metal cutting automation, and several studies have been conducted on tool condition monitoring. At present, several models of wear are known. However, there are disadvantages that metal cutting is a complex process with a variety of criteria. Thus, in this study, the direct approach of tool conditioning monitoring is used, which does not affect the tool, and predictive analysis is used for the Reamining life time prediction.

1.2 Aims and Objectives

There are Some Important Objectives of the project as follows:-

- Develop Experimental Setup for Tool Condition Monitoring using a Machine vision system
- Using the built setup, capture photos of tool inserts in the cutting process.
- To Extract the data from the images captured by the image processing.
- To Develop algorithm and GUI for image processing and neural network for the data prediction

1.3 Background and Motivation

The primary aim of development is to produce commodities efficiently, effectively, and with high quality. Computer Numerical Controlled (CNC) machines are widely used in the metal cutting industry to accomplish this goal while retaining scalable performance. While many conveniences and advantages have been offered with the introduction of CNC in the cutting industry, CNC also has many drawbacks. For example, the problems created by sudden changes in the workpiece can often not be predicted by contemporary CNC machines.

When a tool fails during metal cutting, it may damage the tool holder, the workpiece, or the unit's components. In addition, as machining occurs and the tool wears out, the product's surface strength and dimensional accuracy decrease. Besides, tool breakage can jeopardize the safety of the user or can lead to problems in the production system. . Unexpected changes in the properties of the workpiece material may have a negative impact on the process's efficiency and product quality during turning operations. Modifications in the hardness and dimensions of the workpiece can cause changes in cutting forces, which can lead to increased wear and even breakage of the tool. That wear creates every second new crater or the new increased area of the wear area. This area reflects that there is an increased amount of wear in the tool.

The motivation for Deep learning

John McCarthy is referred to as the Artificial Intelligence Father. He says "AI is The science and engineering of making intelligent machines, especially intelligent computer programs". Artficial Intelligence is the way to make the machine, Robots that are powered by computers or machines intelligently think in the same way as to how a human mind functions. The study of how the human brain functions are the basis for the creation of intelligent software and systems. Different studies have been carried out to explore how a person learns, chooses, and functions when attempting to solve a problem, and these findings have paved the way for AI development.

Same as that way many researchers have used Deep learning and artificial intelligence for tool conditioning Monitoring or Tool wear prediction. Also same as that many researchers are using these Deep learning and AI techniques in various ways with various machining processes like Pimenov [22] Have used the Artificial Intelligence technique with the help of the neural network in Milling machining. In which they have simply collected the data available surrounding like angles of the tool, spindle power, Etc. With this data with the help of several experiments they successfully predicted the life of the milling tooth with some negotiable error. Same as that in many ways researchers have collected the data from various sources like sensors, measurement tools, virtual sensors (camera), etc. This data is used for the various techniques of deep learning and AI. And the by that there are various options like prediction, Monitoring, etc.

In the recent past, artificial neural networks were utilized to build tool wear estimation models. Since now many researchers are using the Neural networks in the Direct and Indirect Methods of tool conditioning monitoring. Artificial neural networks are mathematical model sets that are based on adaptive biological learning analogies and mimic some of the observable aspects of biological nervous systems. The novel configuration of the information retrieval system is the core feature of the ANN paradigm. It is composed of a large number of strongly integrated modules that are similar to neurons and are related to neuronal pathways weighted connections. The ANN layout would become robust for use of large numbers of training cycles.

The motivation for Machine Vision

Machine vision refers to the take information of the scene from the real Scene in the form of a two-dimensional image. There are also some limitations to the machine vision system. To obtain useful information, it must first be determined what is useful information and vision must be used to get the information at all, so that the information is ready to be obtained from the projection, like Image. Data recovery is typically left to a dedicated processor or software in machine vision, but the processor may be thought of as a human being performing the same processing, e.g. calculating wear from the instrument, as in the case of this study. There are many benefits compared to human, machine-based vision processing, such as repeatability, which has led to many technologies used in industry and military.

Cameras, frame grabbers, illumination, artifacts, and processors are the fundamental components of every computer vision device. These basic components enable the system to image the object, i.e. to capture the object's 2D representation, and to extract valuable information from the image. As same many researchers are using machine vision for different applications in the various machining operations like milling, turning, etc. There is also use of machine vision and neural network like rail contact fatigue failure [30].

1.4 Basics of Tool Wear and Tool life

1.4.1 Tool wear

The conventional methods of machining are also known as metal cutting or typical machining processes. Using a wedge-shaped instrument, these operations are typically carried out in the machine shops or tool rooms to machine a circular or flattned job to a desired form, scale, and finish on a raw block of work material. The cutting tool is constrained to travel in such a manner that a sheet of metal is separated in the shape of a chip relative to the work. These machining operations are carried out using different types of cutting equipment on metal cutting machines, most generally referred to as machine tools (single or multi-point). Through this, we can infer that it is also bound to lose some of the material when the cutting tool is increasingly used. And this is referred to as Tool wear.

Figure 1 Image of CNC Tool [24]

The incremental failure of cutting tools due to routine use is tool wear. Tipped tools, tool bits, and drill bits that are associated with machine tools comprise the tools affected. Tool wear induces adverse effects to follow,

1) Higher cutting forces
2) Higher cutting temperatures
3) Inadaquate surface finish
4) Low accuracy of the finished part
5) Can be lead to tool breakage
6) sudden change in tool geometry

The use of lubricants and coolants during machining can help to reduce tool wear. As a result of the reduced friction and temperature, tool wear is decreased. However, since the only reduction is possible and not the total abstention of the tool wear, there will come a time where we need to replace the tool as it directly affects the way the machining is taking place and thus the quality of the final product.

What if we could forecast the moment that we have to replace the instrument to get the full value from it in terms of time, expense, and efficiency with respect to replacing the tool, This Phenomenon referred to as Tool life Prediction, one of the Tool conditioning Monitoring forms more mentioned further in other chapters

Some Major types of tool wear observed on tool inserts[25]

i. major flank wear
ii. minor flank wear,
iii. notch wear at the major cutting region,
iv. notch wear at the minor cutting region
v. crater wear
vi. chipping
vii. tip breakage

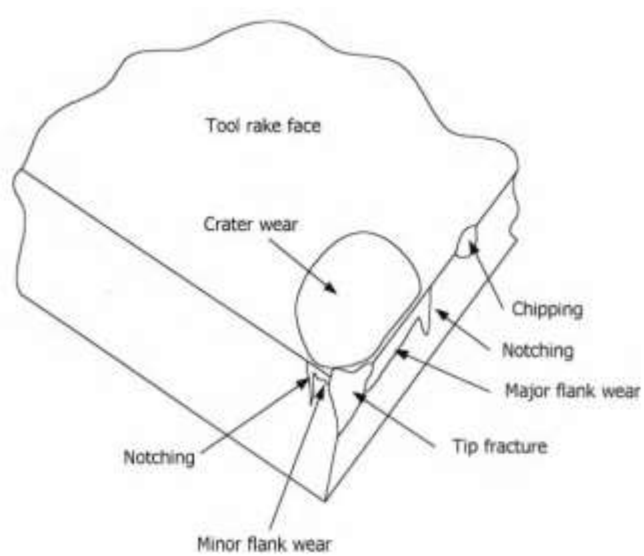


Figure 2 Major types of tool wear onserved on tool inserts[25]

1.4.2 Tool Life

Every system or tool's practical existence. It may work at the end of its useful life, but not effectively. It's also very accurate for a cutting tool. During usage, the instrument loses its substance, i.e. it wears out. As the tool wears down, its productivity decreases. As a result, its life must be established, and at the end of that life, it must be regrounded for new usage. The life of the tool is represented in minutes.[28]

Various ways to define tool life is :

a. The time for two grinding procedures in a row has run out.

b. The amount of time over which a tool cuts satisfactorily

c. The amount of time that elapses since the tool has broken down.

F. in 1907. W. Taylor revealed a correlation between the life of the tool and the speed of cutting, temperature, by keeping the feed constant. A good approximation is given by Taylor's Equation for Tool Life Expectancy.

$$V_c T^n = \mathrm{C}$$

A more general version of the equation that considers the depth of cut and feed rate depth is :

$$V_c T^n d^x f^y = \mathrm{C}$$

Where,Vc = Speed (m/min)

T = Tool life (min)

D = Depth of Cut (mm)

F = Feed (mm/rev)

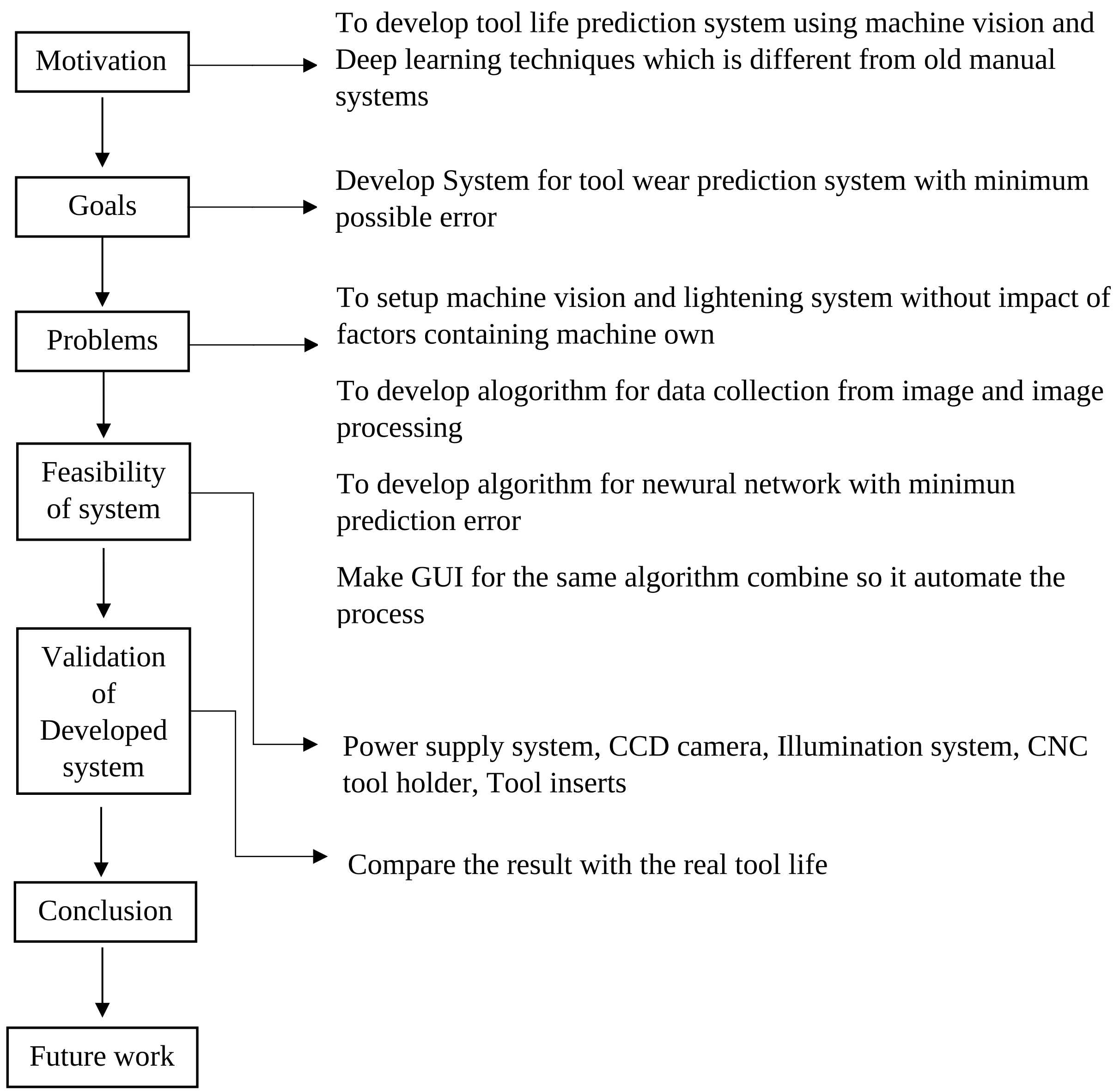
Tool Life Measurements Methods:

The most widely used Concepts for calculating the life of the tool are:

- Machining time
- Actual Cutting time
- Size or the land of wear on the tool surface

- Factors affecting the life of tools:
    i. Cutting speed.
    ii. Feed rate and Depth of cut.
    iii. The hardness of the workpiece.
    iv. The microstructure of the workpiece.
    v. Tool material.
    vi. Tool geometry.
    vii. Type of cutting fluid and its method of application.
    viii. Nature of cutting.
    ix. The grain size of the workpiece.
    x. The rigidity of the workpiece machine-tool system.

1.5 Flow of Research



CHAPTER 2

Review of Literature

In this Era, with an increase in technology, there is an increase in the scope of the automated machining processes. With that, there is a need for the maximum requirement of reliable tool wear and tool life predictions. Tool life prediction usually a time-consuming process and with the material requirement, it is an expensive procedure too. So, it is important to do the prediction of the tool life and decide the replacement time before it creates a crack or any defect or any other catastrophic wear have to stop the machining process and replace the new tool. Prediction of exact tool life also crucial for minimizing the tool cost or the machining cost or time. Tool life is directly proportional to the cutting-edge wear level. If we can maintain the cutting-edge surface and can predict the machining time then also can find the level of the wear of the cutting edge. Many researchers are working on the tool life predictions by various tools and various methods to predict tool life and prevent the defect. Optical microscope measurements or sensors such as the CCD(Charge coupled device) camera, impact, vibration, AE, and power sensors are promising approaches for signal or data acquisition[31,32].

2.1 Prediction of Tool life and Indirect Methods

In these recent years, many researchers have published articles based on predicting Tool wear or the Prediction of the tool life [1-11]. There are mainly two methods for the prediction of tool wear and tool life 1. The indirect method, 2. Direct methods. Many researchers have obtained results from indirect methods. For direct methods, it detects the contour change or the dimensional change for the processing of the data which gives the more precise results but indirect methods there is the use of various hardware if there is the use of the optical method then that optical hardware needs good accuracy for the optical hardware. In more, there is a need to take data at various time-lapses so it automatically reduces the data accuracy due to continual interruption. And also in this there is combination of the methods are also available. Many researchers are doing this type of research and this is affectable in latter type failure [29]

In Indirect methods, Due to the fact that the use of force and AErms signals can detect catastrophic tool failure and a significant amount of chipping at the cutting edge of a tool Flank and crater wear measurement has been a major area of study in machining operations [9-10]. Artificial neural networks have been used in near past for the development of models of tool wear estimation. For both estimating and classifying tool life in turning operations, these models have been created. In these neural network models, cutting forces, AErms, and cutting conditions including rpm, feed, rake angle, and cut depth have typically been used as inputs, but some this of these models have been used in online systems [23,33].

In Indirect methods, as opposed to direct methods to obtain tool conditioning monitoring there is the use of various data signals from the vibrations, temperature, cutting force, and acoustic emission, and other factors. The accuracy obtains by these indirect methods is lower than the Direct methods. S. Karam [6] has used multiple sensor signals for the tool to wear analysis. In which they have attached multiple sensors with Carbide tool which is going to use for the machining of the AISI316 stainless still. After obtaining the Signals they have done preprocessing on the in which they have done cleaning of the signals to eliminate the transient periods and homogeneous signal portions. For feature extraction from this signal, they have used the Wavelet feature function, and then by Neural network, they have approached towards the prediction of the tool life. In the same way N.H. Abu-Zahra [15] have used the Ultrasound waves as signal data. In which they have to use the Ultrasonic pulser/receiver with a bandwidth of 35 MHz (Panametrics PR5900) activated with the transducer which converts the signal into the 10 MHz signals. The tool holder was placed at the back of the tool and between the tool holder with some clearance so it can record the vibration. In the experiment, they have used TNU 334-KC910 and TNU 333-K68 carbide inserts from Kennametal. With that, they also capture the image from the machine vision at some time-lapse. After finding the time of flight and longest travel path they have discredited that waves with the help of the wavelet and the Quadrature Mirror Filter (QMF). This all data they have processed and in the three-layer neural network, then they get the approximate tool life of CNC turning lathe. In various indirect methods to refine the signals or convert the data in another form they use Fourier transform (FFT) and wavelet transform (WT). Because this process gives you feature extraction, feature selection, and both processes are decision-making process data for the Neural network. Same as that various transform is used by Wu[34], in that research they have used multi sensor setup with different six transforms.

2.2 Direct methods and machine vision for Tool wear and tool life

As discussed above Direct methods are more accurate than Indirect methods. In the direct approach, the tool images are used as the data source. Which also includes the approach of machine vision. In this, there is the use of the various gadgets for the various for example T. Mikołajczyk [4] has used CCD-FS-5612p at 684 *512 resolution with aver card. As the same various researcher has used different types of camera and various types of the illumination system. In at end as Indirect methods have to find some feature extraction which can be decision making data.

T. Teshima [18] has defined the color extraction technique. In which they have captured the image from the machine vision system which is attached with the color display. As we know that the with a good amount of illumination system image has a total of 12 colors – (white, Cyan, Blue, Green, Orange, Yellow, Brown, Olive, Red, Violet, Magenta, and Black). This color display gives the image color data. As tool life decreases the image color data have similar changes in the form of increasing or decreasing. So, this data will be the one feature extraction data which is going to use as a decision making data in the 3 layers of the neural network with other data like machining time, velocity, etc.

As same, T. Mikołajczyk [4] have applied color pixels as feature extraction. They utilized a CCD-FS-5612p camera with a 684 * 512 resolution without overscan and an aver card for image compression using the aver compression module. They have settled 12 minutes of the total tool life and then at 1-2 minutes, they have captured the data. With the use of the neural wear software, they have processed the image which is a neural network with the threshold activation function that extracts and analyzes the data of the selected work area. The Output of software is the number of pixels in the X and Y direction. Which will be increased similarly with the wear increasing in the worn area of the tool image. So, this will be feature extraction data for the neural network processing.

There are various ways for the feature extraction in a machine vision system like there is an image feature extraction of the surface texture. Y. Qian [10] have used machined surface texture analysis with the support vector machine algorithm for prediction. For the data, they have taken an image of the machined surface at various time-lapse. After that, they have applied the column projection analysis method and Gabor filter method the extract the features. In the column projection analysis method, it can be applied to the threshold gradient image. This method adds all the pixel values and 2D binary images convert into the 1D array. This obtained array is small data which can be processed for the neural network approach. This data is normalized concerning the largest peak. When the tool is sharp the peak is small with an increament in wear there is an increament in the peak and this data at various time-lapses becomes the data-driven for the wear or life prediction of the tool.

As in this application of the CNC tool, there is the use of the machine vision as same there is various other application. In recent years, the various researcher has published the articles based on the prediction and machine vision which can be also useful for the tool life prediction example X.Suo [20] have predicted the leaf population based on the cotton plant chlorophyll images. In which they have applied the thresholding with the Noise reduction so the background components easily remove. After that, there is the use of the coarse extraction of the image with the red color which directly gives the red color to the cotton plant with fine extraction. This will be the basic RGB color image. There is the value of every Red, green, and blue component. This value of the RGB component becomes responsible data for prediction.

As same, there is one another example which is the shelf-life prediction of the cauliflower. K. Mohi Alden[19] has done image acquisition and then in image processing, they have done segmentation with the help of the OTSU method, after that they have multiplied the binary and RGB image. In this image the at various time-lapses there is a change in the pixel values and this becomes the responsible data for prediction. There is also the use of machine vision method and neural network method for finding leaf population by chlorophyll content [35]

In the indirect method, there is not the only algorithm for the data processing there is a neural network which is also useful for image processing. T. Mikołajczyk[5] has applied the Single Category Based Classifier (SCBC) which is one layer neural network. In that, they're based on the brightness of the wear area and the non-wear area it extracts the features. Firstly, image thresholding applies based on the brightness it defines two types of an area one is Active area – wear area in tool and Non-active area not affected area from the wear. With the increase in time, this area increases and this will be the data for the prediction.

In the same way, for feature extraction E. Alegre [11] they have segmented out the contour of the wear area of the tool. The test was carried out using a CNC parallel lathe. The cylinder components were machined from ANSI SAE 4340 and 4140 steel. The PULLNIX pe2015 b/w camera with 1/3" CCD was used to capture the images. The MATROX METEOR II card is used for digitization. An OPTEM 70XL industrial zoom, a 1X extension tube, and a 0.5X/ 0.75X/ 1.5X/ 2.0X OPTEM lens were also included in this system. FOSTEC DCR R III controlled light and a SCDI to disperse lighting of NER SCDI-25-F0 to avoid shine are used in the illumination system. They have taken 1383 images. These all images have been processed with the signature normalization method which divides the image between the binary image or the descriptor which is the location, size, and orientation of the object in the image. with the increase of the tome, this shape descriptor or signature will be changed and there is also a change in the perimeter of the shape. These perimeter changes also change the vector values of the image. These changing values respectively change with each other in an increase of wear area on the tool. So, this will be the responsible data for the prediction of the tool life or the tool wear.

Like this all the Papers are based on the object recognition tasks based on the different patches description described from an image or there is the use of merge features of the image object recognition in this there is a lot of information is there to process on the result. But if we describe and descript each patch individually that increases the robustness in the process of Prediction of the data and the system can easily find the degree of the tool wear based on the aggregate classified data. So García-Ordás [21] have tried this method for the low-cost tool wear monitoring system which also can be portable. For the low cost, they have used single board computers like Raspberry-pi, OR droid, etc. they have calculated that the on-tool headrest time which is between 5 and 30 min. So, based on that they have derived that the for one tool on head asses time is 0.13 sec so for all tools it is around 4 sec. For image acquisition, they utilized a monochrome Genie M1280 1/3 camera with a resolution of 2592 * 1944 which mounts an AZURE-2514MM lens which is having a focal length of 25 mm and three LED bars lights (BDBL-R(IR)82/16H). By image acquisition and Image cropping, they have derived 254 image datasets of the tool head. Which is extracted from image datasets of 577 images by the Patch labeling and as descriptor Support Vector Machine (SVM) classifier. And by texture descriptors, local binary pattern (LBP), Adaptive local binary pattern (ALBP), Completed local binary pattern (CLBP), LBP variance they have divided the image into the threshold area and the Worn area. So, this can be the data for the next step of the experiments.

2.3 Artificial Intelligence and Neural Network

As industry 4.0 is coming towards the manufacturing sector there is a lot more change with data information by the Big data analytics and data analysis – processing by Artificial intelligence. Based on the recent Deep learning research it will be a revolutionary success for the manufacturing sector. Some methods in deep learning are the most preferred methods like Deep multi-layer perceptron (DMLP), long-short-term memory (LSTM), convolutional neural network (CNN), and deep reinforcement learning (DRL). As data size increasing there is more use and achievement of the Good Results by these methods. When compared to traditional artificial intelligence systems, it looks promising performance in prediction and learning. There is also use of some various hybrid methods Like the GRU model and Hybrid prediction model which are used for long-term predictions and accurate predictions [37].

In both methods of tool monitoring Direct and Indirect methods, there is the use of the Neural Network and Artificial Intelligence. Artificial Neural Network (ANN) is a traditional and effective Artificial Intelligence approach technique. It is made from the inspiration of the human brain neurons. Mainly in the Neural network, there is the use of the deep multi-layer perceptron (DMLP) Which is Multiple Layer ANN. In which there are three layers in the Basic ANN input layer and output layers. The third layer is Hidden Layers which also having a Minimum of two layers in it which is having the main role for the Prediction of the Data. For all this, there is a need for the Input Data. A neural network works in the same way in all the type of data but what we input the data that decides the accuracy of the prediction in Decision-making stage.

As we have seen in the Indirect method can easily get the data from the various sensors like Force sensors, vibration Sensors, Accelerometer, etc. In data acquisition sometimes data generated is in the graph form also like waves. By that waves can generate the data and include it into the input layer of the Neural network. As same Abu-Zahra [15] have used the ultrasound waves. As discussed above there is the use of the longest Travel and time of the path. They have captured the imagination of the ultrasound waves. After that, they used a Quadrature Mirror Filter (QMF) pair, which was developed by Daubechies and calculates the inner product between the coefficients and the discrete sample of the original signal between the delay line, separating the data into low and high frequency components. This results in a tree structure, which is made up of a bank of consecutive bandpass filters that are dispersed logarithmically throughout the frequency spectrum. There are three unique parts to this tree structure: the mark, nose, and flank surfaces. Based on this They turned the input data into a three-layer MLP architecture of ANN with 438 data cases, 220 cases for training, 109 cases for verification, and 109 instances for testing. MLP architecture having the best accuracy for the wavelet form of tree data which near to 94.6%. For training of the network, they have used the Backpropagation Method. They created a mathematical formula based on a comparison between the measured worn land height (machine vision) and the ANN calculated value, based on which they forecasted 40 instances. And they got 95.9% accuracy in this.

In the neural network as discussed above various parameters can be considered for the input of the data in the Indirect method like Some researchers are using output data of the sensor and some are using input data of the CNC machine. As same Natarajan [12] has used the speed of the workpiece(S), feed of the tool (F), depth of cut of the tool (D), and flank wear width (Vb) in his research experiments. In this type of data, there is a chance of less data prediction accuracy also. They have used the Backpropagation algorithm for the training of the data of ANN. The algorithm propagates the data of one output layer to the other input layers with some weight vectors. For all training pairings, the back-propagation approach reduces the squares of the differences between real output and target output units. Weights between the input and hidden layers, as well as weights between the hidden layer and the output layer, are created at random for the selected network topology. They have used 25 patterns to train the data of the ANN. And they have predicted the data mainly there is the use of the PSO methodology for more accuracy of prediction which is based on the number of particles and dimension of particles which decides the weight and this weight gets updated with each layer of the data. And they calculated the accuracy which is near to 96-97% which is better than the back-propagation algorithm.

As we have seen in the Indirect methods there is the use of the various datasets for the input layers of the neural network so same as that there is various way to make data in Direct methods. Indirect methods various types of datasets can be created like Image as the Data. Contour area, Data extracted from the image, Contour image, Color Summarize data, etc. In the extraction of the data from the image, it can be accurate data for the accuracy of the prediction. D'Addona [8] has proposed for the dataset extracted from the AEH gray level image, AEI gray level image, and thresholded black & white image. For the input layer of the gray level image they used characteristics like time, cutting parameters, grey means value, grey median value, grey mode level, standard deviation, skewness, kurtosis. Out of these six characteristics are the main values of the Gray level image. For the black and white image datasets were the number of pixels, maximum white width, plus time and cutting parameters. With the help of MATLAB, they have created the Back-propagation neural network for the training of each data sets, for that they have used function "newff". They found that utilising the proportion of white and black pixels, current cutting input time, and cutting parameters as the NN input an array produced the best results.

2.4 Summary of literature review (Data Collection)

As we can see in the literature review for the More Perfect prediction there is a need for several data. Based on the data collected and data processed in the neural network it gives the result. So different researchers have collected the data from various methods like in indirect methods some researchers are using AE sensors signals, vibration signal, in advance some are using sensor fusion techniques with multi-sensors as same indirect methods also there is the use of various techniques like pixel calculation, Support vector machine, contour periphery, X and Y of the contour, etc. and Direct methods are more effectible due to it is having a deal with real-time data. Then there is a need for data processing and Data prediction for which there is a need for the neural network. There is the use of various neural networks like back-propagation, Convolutional, Double Convolutional, etc. Neural networks are deal with data which we have given input and according to it adds extra weight factor on the next value of the data so some researcher is using extra methods after neural network for more accurate results by modifying this weight factor.

For this collection of data and use of various tools with neural network for prediction of the data more accurately some researcher details are given below in table 1.

Table 1 Observation table of literature

Author	Method	Source of Data	Observation
Abu-Zahra	Indirect method	Decomposed images of Ultrasonic waves	Applied Quadrature Mirror Filter on decomposed images so it converts into binary images data

Alegre	Direct method	Digitalized images with contour extraction	Contour images with labeling
Attanasio	Direct method	Manually collected data from peripheral wear measurement	Used a response surface methodology and ANN for prediction
Yoo	Direct method	Data collected from the features of images of bearing with time-frequency	Faded image features in Continuous Wavelet Transform and Convolutional Neural Network
Qian	Direct method	Data collected from the image of the texture of the machined surface	Compared to a Backpropagation and support vector machine techniques and get an error of 2.45 % between them
Natarajan	Indirect method	Collected data from the depth of cut and feed	Used Backpropagation ANN with population-based stochastic optimization technique for reducing error
Gadelmawla	Direct method	Data from texture features of Gray level image	Used image texture of the gray-level co-occurrence matrix and the machining time with an error of 4.69%
Sidahmed	Direct method	Data of Gray level image	Used RAPID-I machine vision system and data from Gray level value of the image
Mehta	Direct method	Data collected from an image pixel matrix	Converted the image into the binary and collected data of pixel matrix from MATROX software
D'Addona	Direct Method	Collected Data from Flank wear and Crated wear images of tool	They have collected three Different images of tool two are gray level and

			other is B&W. by Matlab collected matrix data and by backpropagation ANN for recognition of the cycle
Yang	Indirect method	Collected data from vibration signals	Used a Doble Convolutional neural network to analyze the two signals under two different noise conditions
Karandikar[27,36]	Indirect method	Collected data from various spindle speeds	To predict the constants in Taylor's life used Bayesian inference with the Metropolis-Hastings algorithm
Karam	Indirect method	Used various sensor signals as data	From signal have extracted features by wavelet feature extraction and made cognitive decision-making algorithm by backpropagation ANN
Castejón	Direct method	Use of tool segmented tool images	From the segmented tool, images collected the shape of the geometric descriptor and classify it by linear descriptor analysis

CHAPTER 3

Tool Life Prediction Methodology using Machine Vision and Neural Network

In this Chapter, Methods of Tool life prediction is explained using machine vision and Neural network – Direct Approach. Implementation and explanation of the experiments are discussed in Chapter 4.

Mainly there are Three requirements for prediction of tool life using machine vision are :

I. Image Data Acquisition

II. Data Extraction from image

III. Data processing in Neural Network

So, This Chapter three main Sections as Discussed Above.

3.1 Image Data Acquisition (Machine Vision)

In a direct Approach, Data Acquisition is done by the machine vision system. It is the generation of a two-dimensional image from the Real-world model. A machine vision system (MVS) is a type of technology that allows the inspection, evaluation, and detection of still or moving images by a computing device. In machine vision, there is a connected computer or dedicated processor is there which use for information gathering and recovery purpose. To acquire images, machine vision systems developed with digital sensors encased within industrial cameras with improved optics, so computer hardware system and software system can process, interpret, and give output in different decision-making features [44].

Machine vision systems, also known as automated vision systems or vision inspection systems, are made up of various modules that are comparable to those found in other systems. Furthermore, each of these components has a specific purpose and may be employed in a variety of other systems; nevertheless, they each play a unique function in a machine vision system when working together.

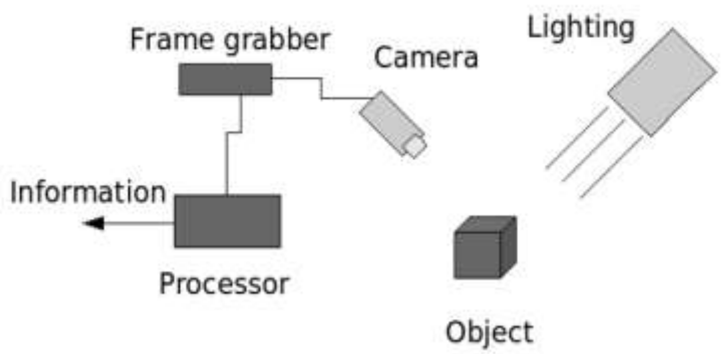


Figure 3 General Machine vision System

The following five items usually include these components in machine vision systems:

I. Lightening system
II. Lens or Optical system
III. The sensor
IV. Frame grabber
V. Information Communication System

In the lighting system, the choice of lighting which is use in a machine vision device should be made to optimize the contrast for calculating or observing which characteristics are of importance while minimizing the contrast of all other characteristics of the component. To achieve this goal, it may be necessary to change the amount of light utilised (intensity), the lighting style (dome vs. ring light, for example), and the positioning of the light source relative to the component and the optical device or camera. By altering these precise variables, a machine vision device's capacity to reliably characterise and quantify the feature(s) of the component being tracked would be considerably enhanced. Lighting options for obtaining images with fast shutter speeds include LED lighting and stroboscopic lamp.

The optical components of a machine vision equipment are generally a lens or a camera that combines the lens with other pieces, such as the sensor. The lens collection will determine the field of vision, which is the two-dimensional region across which observations may be performed. The lens will define the focusing depth and focal point, both of which are relevant to the capacity to observe details on the portions processed by the system. For tool wear data processing as a camera, there is mainly the use of the CCD (charged coupled device) camera and the other was a CMOS (Complementary Metal Oxide Semiconductor) camera. Higher dynamic range and greater resolution are typically provided by CCD. It is widely accepted that poorer image quality would result in lower precision and repeatability of measurements. Plus, the electronic shutter inherent in CCD removes the need for a mechanical shutter. CMOS is used for faster performance, lower power consumption, and more integration capability. With global shutters or snapshot shutters, certain CMOS can now capture photos of moving objects without distortion..

Sensors in computer vision systems gather light from an optical device and convert it to a digital picture. Sensors employ CMOS or CCD technology to gather light and convert it into a sequence of pixels that represent the existence of light in various places of the original component being viewed. Sensors are measured by their resolution, which is a measure of the number of accessible optical image pixels. Higher resolution sensors may provide pictures with more pixels, resulting in improved picture quality and the capacity to resolve information. The sensor resolution is determined by the dimensions of the components being measured, the dimensions of the measurements themselves, the tolerances of those measurements, and other device factors. Higher resolutions will improve the accuracy of measurements taken by the machine vision system.

With a camera, a frame-grabber is used to convert an analog signal to digital images from the camera. Analog-to-digital converters that quantify the analog signal received from the camera are involved in this process. The process is generally integrated with the camera in modern cameras, which can output the digital image through a digital bus.

Once the vision processing component has finished its tasks, the communications protocol is the final piece in the machine vision system. The goal of this element is to give a useful output in a defined format that can be used to drive other components in the manufacturing process using the output from the vision processing system. In industry, there is the use of the various standard I/O devices using PLC and various machines. As in the experiment, there is the use of the simple standard cable which transfers the image data to the Computing Processor.

Understanding the physics and capabilities of machine vision systems can aid in determining if an application is suited for camera-based systems. In general, whatever a human eye can see, a camera can see (sometimes more or less), yet deciphering and reporting the data can be difficult. Using a vendor that is familiar with systems, lighting, and approaches may save a lot of time and money in the long run.

3.2 Data Extraction from image

As we have seen in the Chapter 2 literature review there is the use of the data extracted from the experiment result use for the decision-making, so data extracted from the Experiment results make an important part of the decision-making process. So, in the optical method, there is the use of various methods. Data acquisition is frequently utilized in inspections to establish a "pass or fail" for comparison with target values..

From research, A list of some methods that can be used to obtain information about the target is as follows:

- Pixel Counting
- Edge Detection
- Gauging
- Pattern recognition
- Blob Detection
- Color analysis

In Pixel calculation, there is the use of various image processing techniques like thresholding of image, Gray level and also before that for preprocessing there is the use of the several filters like a median filter, Gaussian filter, bilateral filter, Non-local mean filter, etc. The smallest part of an image is the pixel. Each pixel is equal to any single value. In an 8-bit image with a greyscale, the pixel size is between 0 and 255. At the precise position, each pixel stores a value equal to the intensity of the light. So after the several image processing techniques according to intensity pixel converts into the black and white image as shown in image 4 so we can calculate the pixel of a particular part of the image according to the intensity. Data collected from this number of the pixel of the worn area [41].

Figure 5 image obtained after thresholding, filtering, dilation, erosion [39]

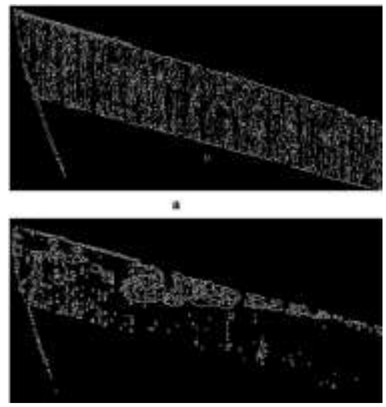


Figure 4 Extracted worn area pixel at different time in tool

Edges are called sudden modifications of discontinuities in an image. Important transformations are called edges in an image. As margins, major transformations in an image are called edges. The majority of the form elements of a picture are surrounded by corners. So, first detect these edges in a picture, then use these filters to improve particular picture sections that include edges, and the picture sharpness will increase, making the picture sharper. Some operators use for the edging are Prewitt operator, Sobel operator, Robinson compass operator, kirsch compass operator, Laplacian compass operator. Data collected from this method is the Periphery of the particular worn area.

A gauging machine vision system measures the distances between two or more points or geometric positions on an object and decides if the criteria are satisfied by these measurements. If not, the vision device sends a warning of malfunction to the computer controller, allowing the target to be expelled from the line by a rejection process. So in this process, data will be collected by two lines in the image like X and Y so according to the worn area with increasing in the worn area there is a change in the value of X and Y so that will the Decision making data for prediction [40].

Recognition of patterns includes researching image recognition and many other areas including machine learning (a branch of artificial intelligence). Image processing is used in pattern recognition to recognize the objects in an image, and then machine learning is used to teach the algorithm to modify patterns. In tool wear analysis there is very little use of pattern recognition as especially in direct methods. In indirect methods, there is the use of the data pattern recognition with the fuzzy network, convolutional network, etc.

In machine vision, the methods of blob detection are aimed at identifying regions that vary in properties, such as light or color, in a visual picture relative to neighboring regions[45]. It can be the texture blob too. Informally, a blob is an image region in which some properties are constant or roughly constant; in some way, all the points in a blob can be assumed to be similar to each other. Convolution is the most popular strategy for blob detection. By various methods and image processing techniques this blob can be detected and also for the tool wear calculation there is the use of blobs using shape descriptor.

In machine vision, the color analysis method is mainly used in vegetable or flower type detection or prediction analysis. In every image, there are many different color space representations: CIE, RGB, YIQ, YPbPr, HSI, CMYK. In every image particular object have the same color or color intensity. So, there is an algorithm available call color summarizer. Which gives the 12 basic color percentages. This particular gives the percentage of space of the object in the image. Also, it calculates the percentage of color pixels. In some research for flower detection or leaf detection, the image converts into the binary colors or apply the filter of Red color space do it will detect the image with particular color so we can detect the leaf percentage from the color percentage of the image.

3.3 Data processing in Neural Network

In image processing, there is the use of the various neural networks and other techniques for prediction and data mining like support vector machines (SVM), Gaussian mixture models (GMM), k-NN classifiers, etc. Neural networks work like neurons in the mind. By taking a series of binary inputs (nearby neurons), the Perceptron models the neurons in the brain, multiplying each input by a constant valued weight (the synapse intensity for each nearby neuron), and thresholding the total of these weighted inputs to generate a "1" if the sum is sufficiently high and otherwise a "0".

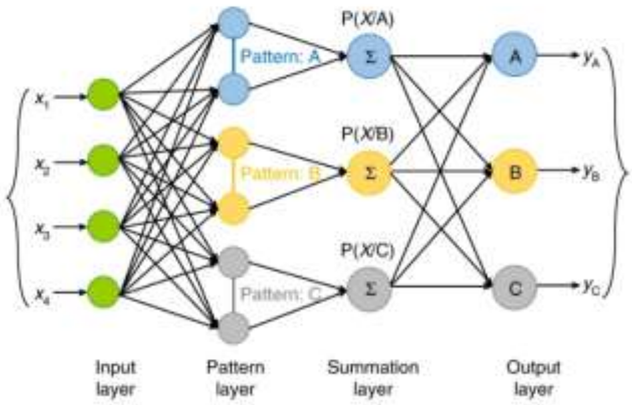


Figure 6 Structure of neural network [42]

As shown in fig 6 there are mainly three layers of the neural networks input layers, pattern layers (hidden layers), output layers. It makes the decision tree according to data. In the input layer, it takes the data according to decided decision-making data then there is the pattern layer and summation layer which are also called hidden layers. In which data will be processed and according to that data it will be adding some weight to the next layer and makes the output layer. Several widely used neural networks are discussed below.

Probably the most commonly used neural network used in computer and machine vision applications is CNN. Multiple explanations exist for this. Second, the CNN's architecture is intended to more closely resemble the human visual brain and pattern recognition processes. This is feasible because CNN is divided into multiple neural stages that perform different activities. Convolutionary layers are used to extract features, same as convolutional operators are used to locate features like edges.. In traditional image processing, image filters like Gaussian blurring and median filtering perform this function. CNN designs, on the other hand, are modelled after the human visual system (HVS), which uses retinal production to extract features such as edge detection. Also, the convolutional network is also used to forecast data, such as pattern recognition.

Next is BPNN (backpropagation neural network) which is ANN (Artificial neural network) and a widely used neural network to predict the data in both Direct and indirect methods. As a solution to the problem of training multi-layer perceptron, the back-propagation neural network was developed by Rumelhart et al. The fundamental developments represented by the BPNN were the inclusion in each node of the network of a differentiable transfer function and the use of error back-propagation to change the internal network weights after each training cycle. The BPNN was used as a classifier primarily because of its capacity in the feature space to create complex decision boundaries. There is also work suggesting that a BPNN can estimate Bayesian posterior probabilities at its outputs under suitable conditions. The BPNN was used as a classifier mainly because of its ability to establish complex judgment boundaries in the function space. There is also work suggesting that under appropriate circumstances, a BPNN will approximate Bayesian posterior probabilities at its outputs. And researchers guarantee that there will be less than 10% error using BPNN.

Then there is fuzzy logics which combine with neural network and make Fuzzy neural network, there are several aspects in common with both neural networks and fuzzy systems. They can be used to solve a problem where no statistical model of the given problem exists (e.g. pattern recognition, regression, or density estimation). They only have some negatives and benefits that vanish almost entirely when integrating all definitions. Fuzzy neural networks are mostly used in indirect systems and online systems to predict the data.

So mostly the used data types are linear but sometimes there is the use of non-linear data types so neural network error can be increased in prediction so there is the use of a different type of analysis like SVM (Support vector machine). Vapnik et al proposed a novel learning system based on the support vector machine, which is developed based on a finite number of samples of information obtained in the present training text to produce the best classification results based on mathematical learning theory[43]. A support vector machine creates a hyperplane or set of hyperplanes in a high- or infinite-dimensional space, which may be used for grouping, regression, or other tasks like outlier detection. Intuitively, the hyperplane with the largest distance to the nearest training data point in each class performs a successful separation since, in general, the higher the margin, the smaller the classification or separation error.

CHAPTER 4

Image Acquisition and Image Processing system implementation

The aim of this research is to find the cutting parameters that affect tool life and, based on that, develop an algorithm to predict a tool life. Tool life is associated with incremental wear, also defined as flank wear. When the maximum flank wear value is reached. The tool's life has come to an end. As a result, flank wear must be assessed in order to determine tool life. The series of techniques that can be used to calculate flank wear is known as digital image processing. The camera first takes the picture. Following that, the image is processed using different techniques to classify and quantify the wear area. This chapter discusses the steps proposed for processing a tool picture with the aim of identifying total flank wear.

4.1 Image Acquisition

The camera Sensor is an effective hardware interface between the object and its image. In industrial camera systems come in a wide range of configurations like CMOS and CCD. The camera system is made up of the camera sensor, the Lens, and the Illumination system. The device components were chosen based on the specifications of the tool state monitoring system. For the Image Acquisition, the Image is taken when the system is placed on a CNC machine, and when required machining is finished, the tool can be settled in Infront of the camera so the camera can take photos. The wear can be Range between 50 microns to 2000 microns, so there is the requirement of Micro Photography.

4.1.1 Material and Measures

The machining was done on an 'HMT CNC Turning' lathe using a cutting tool PSSLNR1616H12 with a cemented carbide insert coated SNMG 120408 WIDIA brand and a cutting tool PSSLNR1616H12. The CNC turning machine can be configured in the following ways : Rpm & feed limit - 1500 rpm & 5000mm/min, 3kW Power capacity. Machine experiments were carried out on ten similar inserts with four tips from the same batch, without lubrication, and under the following cutting conditions of Design of Experiment:

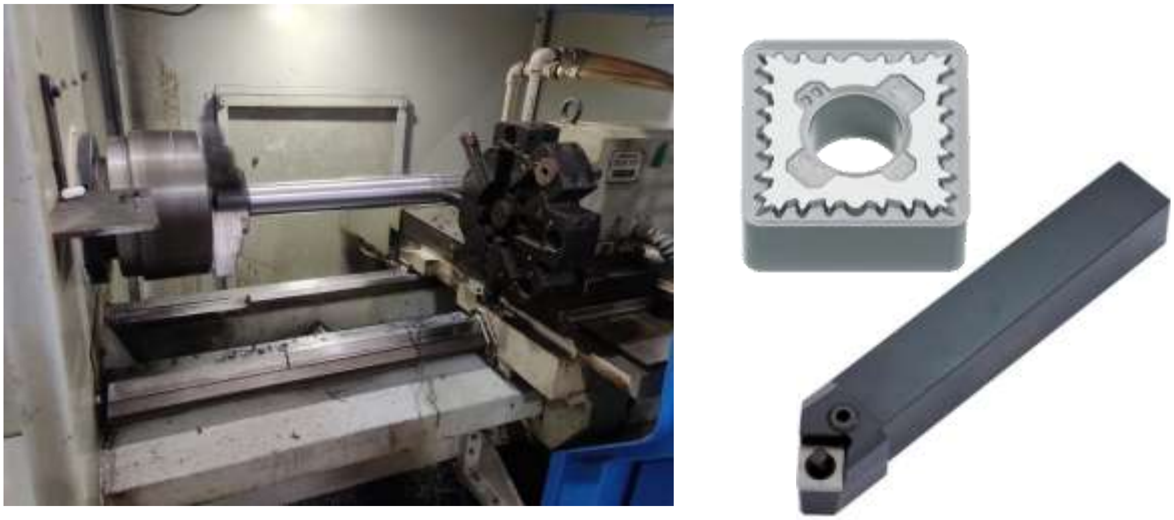


Figure 7 HMT CNC Turning lathe, CNC tool and Insert

Table 2 Design of Experiment

Cutting speed (mm/min)	Feed (mm/rev)	DOC (mm)	Percentage/Number of White Pixel						
			TML – 200mm	TML – 400mm	TML – 600mm	TML – 800mm	TML – 1000mm	TML – 1200mm	TML – 1400mm
70	0.1	0.3	496	758	881	990	1029	1460	1832
70	0.15	0.4	872	987	1274	1511	1931	-	-
70	0.2	0.5	987	1351	1487	1832	-	-	-
80	0.1	0.4	746	994	1197	1676	2006	-	-
80	0.15	0.5	778	989	1145	1604	1984	-	-
80	0.2	0.3	779	991	1462	1917	-	-	-
90	0.1	0.5	799	984	1460	1856	-	-	-
90	0.15	0.3	734	957	1344	1698	1945	-	-
90	0.2	0.4	758	987	1087	1505	2060	-	-
TML: Total Machining Length (Photo will be taken after every TML length of machining. It can be vary based on tool life and breakages)									

The material chosen is an AISI 4140 cylinder with a hardness of 34 HRC, dimensions of 250 mm long and 50 mm diameter, and tensile and yield strengths of 615 MPA and 414 MPA, respectively. The Spectrographic Report Given below:

Table 3 Spectrography Report AISI 4140

Spectrography Report		
	Result	Required
% Carbon	0.41	0.38-0.43
% Silicon	0.22	0.15-0.35
% Sulphur	0.022	0.040 max
% Phosphorus	0.025	0.040 max
% Manganese	0.76	0.75-1.00
%Chromium	1.078	0.80-1.10
%Molybdenum	0.23	0.15-0.25

Figure 8 AISI 4140

4.1.2 Image Acquisition System Configuration

Based on the system parameters and the availability of system components, the following components were chosen for Image Acquisition, as seen below:

1. Camera Sensor:
   Figure 9 shows the 'Baumer EXG50 Monochrome Color Camera' with CMOS Sensor, 2592×1944 pixels resolution, 5MP brightness resolution, and 14 frames per second frame rate. We choose this camera because of its compact design, higher frame rate, short shutter time, compatibility with both hardware and software trigger systems, and other features.

Figure 9 Baumer EXG50 Monochrome Color Camera

2. Camera Lens:

Figure 10 shows the 'Computar-TEC-V10110MPW', a Bi telecentric lens with a magnification of 1X, a focal length of 110.2 mm, and a distortion of 0.015 percent. We choose this lens because all rays passing through an object in a Bi-telecentric lens would be parallel in the camera sensor, allowing them to penetrate regardless of the field of depth.

Figure 10 Computar-TEC-V10110MPW

3. Illumination System

Figure 11 shows an illumination device with a 9-10 Watt illumination range, intensity regulation, white color light, lens mount on Camera, and an internal-outer diameter of 50 mm-100 mm. It has a brightness that can be adjusted from 10% to 100%.

Figure 11 Tolifo-R-160S white color Illumination System

4.1.1 Setup for the Image acquisition in the CNC machine

The primary function of the camera mounting in CNC machines is to hold the camera, lens, and LED, so after the tool completes a certain amount of machining length, it returns to the front of the camera and lens mounting, where the camera can conveniently click the image of the tool's flank wear. The system's position is constrained by the carousel's ability to shift and rotate. The system had to be placed behind or side the spindle in this case so that it didn't come into contact with the carousel or its equipment at some time. The system was initially positioned closer to the spindle such that the photographs captured both the tool's face and main flank. As a result, the specification and the actual model of the Stand for Camera, Lens, and LED Light are being developed according to the requirements shown in Fig. 12. SOLIDWORKS 2017 was used to build this Stand Model. Acrylic sheets with a thickness of 6 mm were used to create the final model, as shown in fig 13. And the Base support plate is made from the Iron Plate of 4mm.

This setup is attached to a Computer Device, which serves as the storage unit, Frame Graber, and Information communication system for this machine vision system. The device has a Windows operating system and is equipped with a 2.4 GHz Intel Core 5 Duo processor and 8 GB of RAM (Random Access Memory). It also has Baumer camera Explorer Software for camera triggering. The software triggered the Baumer CMOS Camera Sensor. Whenever the trigger is open, the camera takes a picture of the current situation, which the device saves with a grey filter. The camera system is operated by 12 V DC, while 9 V DC powers the LEDs.

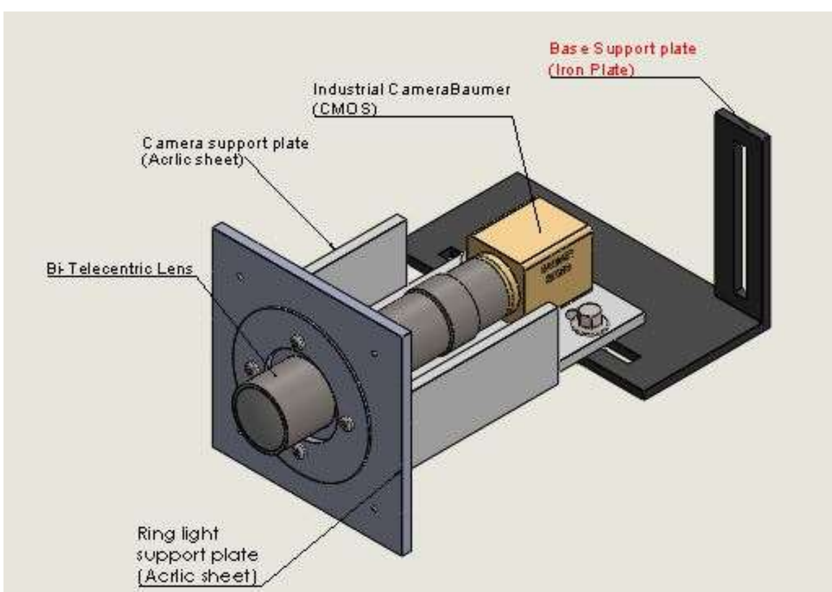


Figure 12 Solid work model of Camera Stand

Figure 13 Setup for Stand for Camera, Lens and LED

4.2 Image Processing

To transform an image into data, various and multiple image processing techniques are used, with several processes resulting in pixel counts or pixel values. To minimize image processing time and memory constraints, the processing area of the captured image is limited to the region of interest. Here, the critical goal of the image processing stage is to remove the wear area from the image of the cutting tool insert that was collected during image acquisition. As can be seen in figure 14, it is a grey level image that can be taken by the sensor, in which the grey level at the worn region has high values, making the worn area differentiable. Based on this, an algorithm to calculate the worn area pixel has been created.

Figure 14 Gray level Worn out tool image

So, in this algorithm, there is the use of mainly three steps after cropping of Image of worn-out area are,

1. Image Denoising
2. Image Histogram Enhancement
3. Image Thresholding

1. Image Denoising

The fundamental purpose of image denoising is to approximate the original image by removing noise from a noisy picture representation. Image noise can be caused by various internal (sensor) and external (environment) factors that are difficult to prevent in real-world environments. Image noise is a sudden alteration of light or color in a picture that is usually caused by electrical noise. The image sensor and circuitry of a scanner or digital camera can produce it. It's a form of picture noise that can't be avoided.

In this step, there is the use of a Bilateral Filter going to be used to remove noise from the picture. A bilateral filter is a non-linear picture smoothing filter that keeps edges sharp while removing noise. To override the intensity of each pixel, it employs a weighted average of intensity data from surrounding pixels. This weight may be calculated using a Gaussian distribution. The weights are influenced not just by the Euclidean distance between pixels, but also by radiometric variables such range discrepancies. The weights are calculated not just by the Euclidean distance between pixels, but also by radiometric variances such as colour intensity, depth distance, and other range changes. Sharp edges are preserved as a result. In worn out area there is mainly a sharp edge so this filter can be very useful to extract out it.

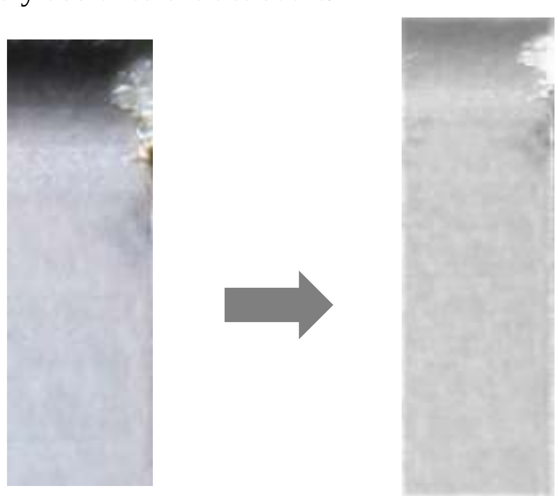
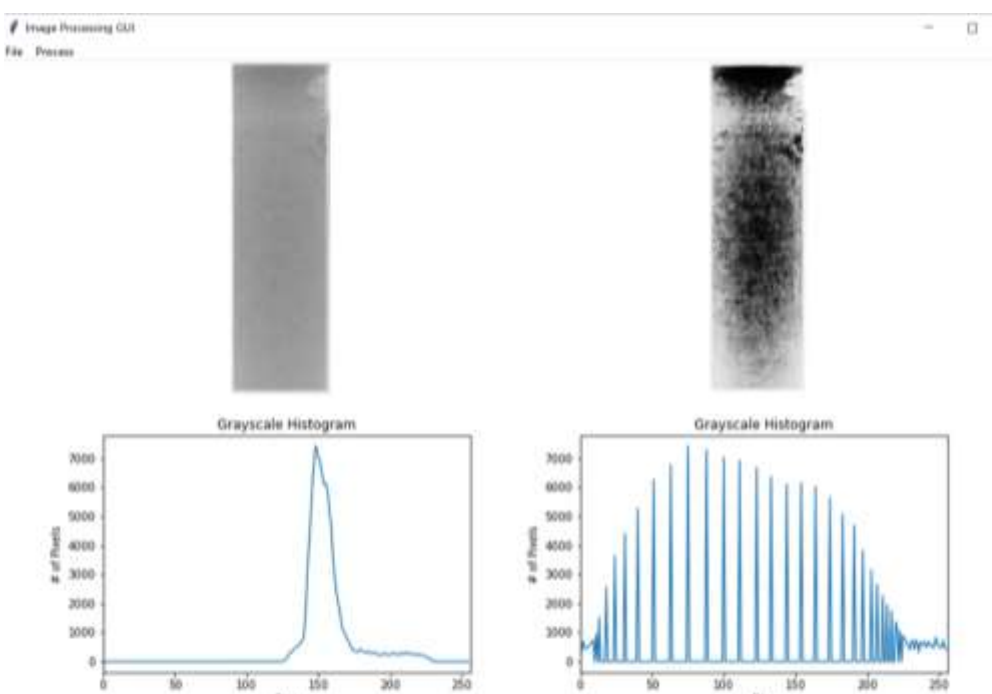


Figure 15 Bilateral Filter

2. Image Histogram Enhancement

The histogram Equalization is a technique for improving picture contrast in digital images. It accomplishes this by effectively spacing out the most frequent intensity values, or extending the intensity spectrum of the image. This approach often raises the global contrast of photographs when close contrast values describe the available data. This allows locations with low local contrast to achieve success.

In these procedures, Histogram Equalization is used to differentiate the average grey level of the worn-out region from that of the unworn region pixels across a generally constant interval, with the original gray-level gap being mapped into a fixed interval of 0 to 255 via a linear transformation. There is also the usage of adaptive Histogram equalisation in this case. An adaptive Histogram is a form of the histogram that adapts to the adaptive approach. It's not the same as histogram equalisation. It creates numerous histograms, each corresponding to a distinct area of the image, and utilises them to redistribute the brightness values in the picture. As a result, it's great for increasing local contrast and enhancing edge definitions in various regions of a photograph. Figure 16 shows the Adaptive Histogram Equalization interface of Graphical user interface developed in python.



3. Image Segmentation

Image Segmentation is the method of partitioning a visual image into different subgroups (of pixels) called Image Objects, which reduces the image's complexity and makes image analysis easier. We use various image segmentation algorithms to break and group a specific collection of pixels from an image. By doing that, we're simply attaching marks to pixels, and pixels with the same mark are grouped together because they share something in common.

In machine vision, by segmentation of image, the captured image segment into various regions, such as the background and foreground, an unworn region of cutting tool inserts, and a wear region of cutting tool inserts. The primary goal of image segmentation is to locate the wear area where the cutting tool inserts the image. Here we are using one of the segmentation methods called OTSU's thresholding, and Binarization based method in which is it directly gives the Binary image of the worn-out area. According to Otsu binarization, it approximately takes a value in the center of such peaks as the image's threshold value. In simple terms, it uses the image histogram to calculate a threshold value for a bimodal image. Otsu's approach is a discrete one-dimensional variant of Fisher's Discriminant Analysis, is similar to Jenks's optimization method, and is analogous to a globally optimal k-means implemented on the strength histogram.

So, after the Otsu thresholding, only two values pixels will be remained (0,0,0) and (255,255,255) called binary image Figure 17 shows the threshold image of the tool by OTSU's Thresholding and binarization method.

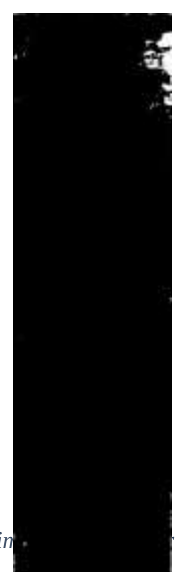


Figure 17 Binary in Otsu's Thresholding

4.3 Data Extraction

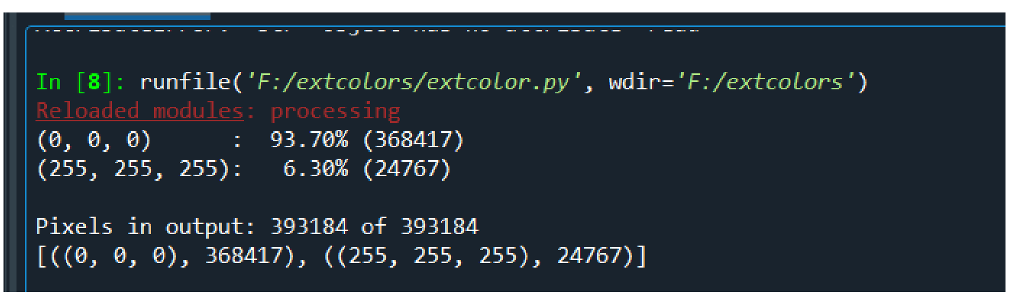
After the image segmentation, there is only two values of pixels there one is black and other is white pixels both have pixels values according to their intensity matrix. And as shown in fig. 17 white area is the worn-out area, so there is a need to count white pixels in the image, so based on that, in different images, white pixels count vary.

So, for that, there is the use of the EXTCOLRS Command to develop algorithm. It is CIE76 (International Commission on Illumination) Formula based algorithm. The 1976 formula was the first to link a colour difference measurement to a set of CIELAB coordinates. Because the CIELAB space was not as perceptually homogeneous as expected, especially in the saturated areas, this formula was superseded by the 1994 and 2000 formulations. This indicates that this formula gives these colours a higher rating than other colours. The delta E value for,

The CIE76 colour difference formula is given as for two colours in CIELAB colour space (L1, a1, b1) and (L2, a2, b2):

$$\Delta E_{ab}^{*} = \sqrt{(L_2^* - L_1^*)^2 + (a_2^* - a_1^*)^2 + (b_2^* - b_1^*)^2}$$

According to this, for figure 17, pixel count in the developed algorithm in python showed in fig. 18, which shows the percentage of pixel value (0,0,0) and (255, 255, 255) with total pixel count.


```
In [8]: runfile('F:/extcolors/extcolor.py', wdir='F:/extcolors')
Reloaded modules: processing
(0, 0, 0)      :  93.70% (368417)
(255, 255, 255):   6.30% (24767)

Pixels in output: 393184 of 393184
[((0, 0, 0), 368417), ((255, 255, 255), 24767)]
```

Figure 18 Pixel calculation result in developed algorithm

4.4 Flow chart of steps of Algorithm for image processing and pixel calculation

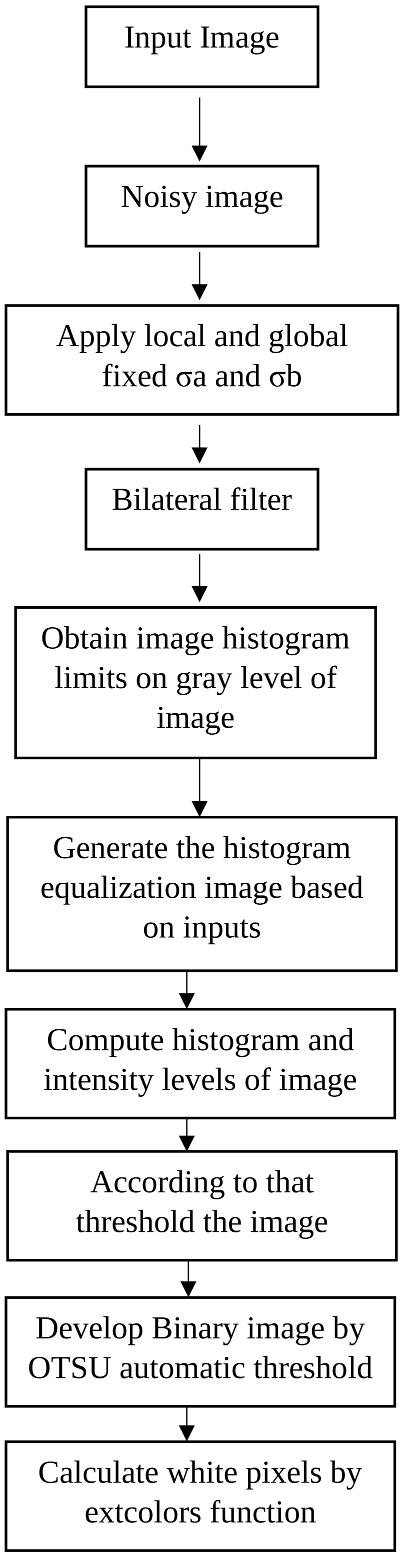


Figure 19 Flowchart of algorithm steps

CHAPTER 5

An Artificial Neural Networks Based Tool Prediction System

An artificial neural network (ANN) is a data-processing algorithm or paradigm that is influenced by by the human brain's tightly interconnected, parallel structure. ANNs are integrated arrays of mathematical models that mimic some of the observable features of biological nervous systems and rely on biological learning analogies. The ANN paradigm's important element is the unique configuration of the information processing system. It is made up of a large number of highly integrated processing components that work similarly to neurons and are connected by weighted connections that work similarly to synapses (see Figure 20).

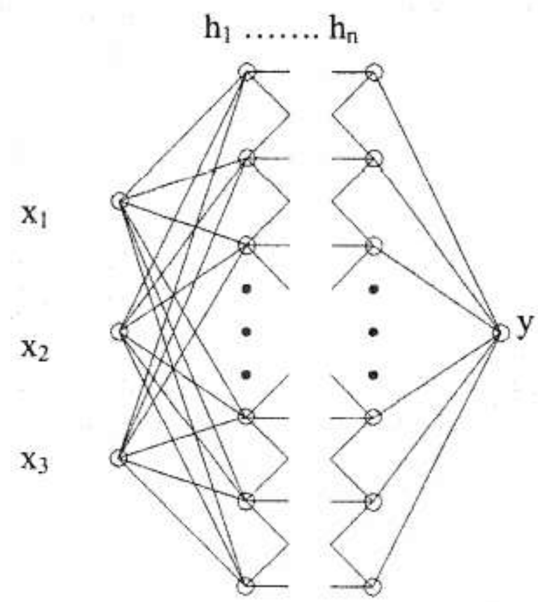


Figure 20 structure of the artificial neural network in the back-propagation algorithm

The ANN would go through a lot of learning cycles in order to function correctly. The back-propagation learning process is the most reliable among popular ANN implementations. Back-propagation training is an iterative gradient approach aimed at reducing the mean square error between the actual output of the hidden layers and the intended output. It necessitates the existence of constant differentiable non-linearities. A sigmoid logistic function is the most often used non-linearity in the back-propagation algorithm. An algorithm is showed in Appendix.

$$f(\alpha) = \frac{1}{1+ e^{-(\alpha-\theta)}} \quad (1)$$

Steps to generate the Back-Propagation Artificial neural network are:

1. Input and adjust Data Set
2. Neural Network Selection
3. Training of Data set
4. Model analysis based on Data
5. Calculate output and error calculation

5.1 Input and adjust Data Set

The data used to create the predictive model is included in the data collection. It consists of a data matrix in which columns and samples represent variables are represented by rows. A data set's variables may be one of three types: The independent variables are the inputs. The dependent variables are the targets; the unused variables are not used as either inputs or targets. Training samples, which are used to build the model; selection samples, which are used to find the optimal order; and testing samples, which are used to validate the model's functioning are all examples of samples. and unused samples (those that haven't been utilised at all).

Here, the total 150+ samples and columns can be represented as Cutting Speed, Feed, Depth of Cut, White pixels, Remaining Tool life (RTL), and wear amount. The first four are considered the input values for data set and neural network, them other two are considered the Target values that the neural network predicts after the training.

The uses of all the samples in the data set are depicted in the pie chart below. There are 150 samples in all. The total number of teaching samples is 80 (60.6%), the total number of collected samples is 26 (19.7%), and the total number of research samples is 26. (19.7 %).

Mainly the Remaining tool life and wear is going to have more variation according to the white pixel count. The Scatter chart for the same is shown in fig 22.

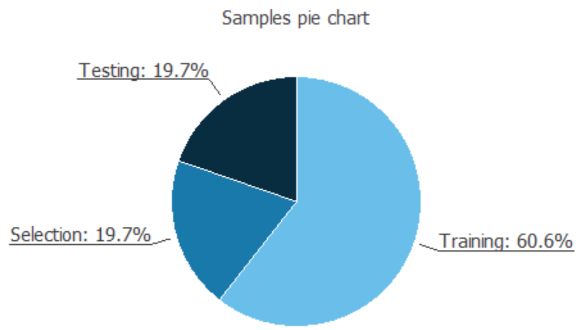


Figure 21 Sample Distribution Pie Chart

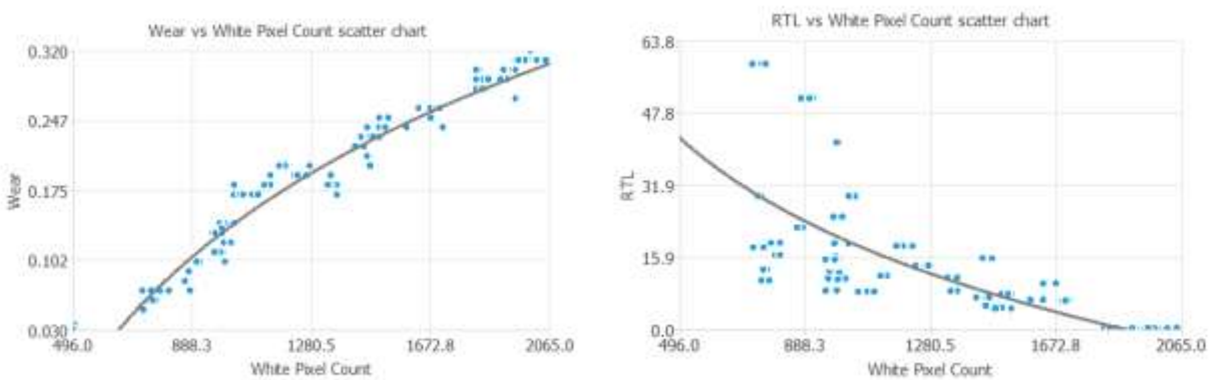


Figure 22 Scatter chart for the wear - white pixel count and RTL - white pixel count

5.2 Neural Network Selection

The neural network represents the predictive model. Deep architectures, a form of universal approximator, are supported by neural networks in Neural Designer. Neural Network architecture is mainly based on the five types of layers: Perceptron layer, Scaling layer, Unscaling layer, Bounding layer, Probabilistic layer.

The most important layers of a neural network are the perceptron layers (Deeply connected layers). The neural network is able to learn as a result of them. The perceptron neuron receives the data as a sequence of numerical inputs x1,...,xn. To create a single numerical output y, this data is combined with a bias b and a sequence of weights w1,...,wn. The neuron's parameters have bias and weights. This neuron calculation depends on the perceptron layer.

The combination function takes a number of input values and converts them into a single combination or net-input value.

$$combination=bias+\sum weights\cdot inputs$$

In terms of its variation, the activation function determines the perceptron output.

$$output=activation(combination)$$

The neural network's role is determined by the activation function of the perceptrons that make up each layer.

The total two perceptron layers and total 12 neurons with Sigmoid Function are used here. As a result, the Sigmoid Function and Rectified Linear Activation Function (ReLU) can be used to trigger the perceptron. In a back-propagational neural network, the Sigmoid Function is used (BPNN). It Gives more smoother output than the other functions. ReLU function is also the most used activation Function in the Neural network world Right now. ReLU function is better than other function is due to it overcome the vanishing Gradient Problem.

In the context of neural networks, the scaling function can be assumed seen as a layer connected to the neural network's input data. The scaling layer includes some essential input statistics. The Minimum – Maximum approach is used here, which is a conventional and appropriate way for this type of data.

The bounding layer and Un-scaling Layer are connected with the output layers, which contains some amount of statistical methods for deviation in values. Following that is a schematic description of the network architecture. A scaling layer, a neural network, and an un-scaling layer are all used. Scaling neurons are yellow circles, perceptron neurons are blue circles, and un-scaling neurons are red circles. The number of inputs is four, and there are two outputs.

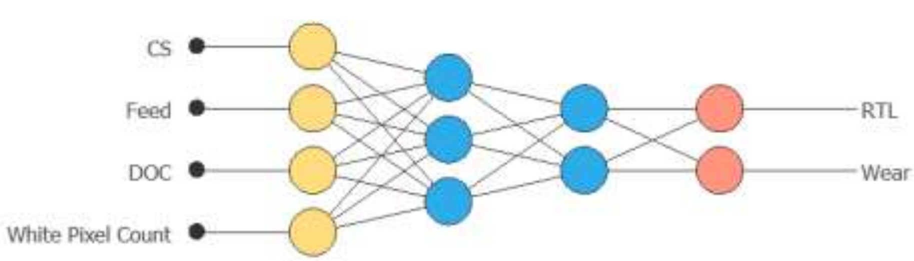


Figure 23 Basic ANN Architecture

A schematic illustration of the resultant deep architecture follows. Figure 24 depicts the employment of a scaling layer, a neural network, and an unscaling layer.

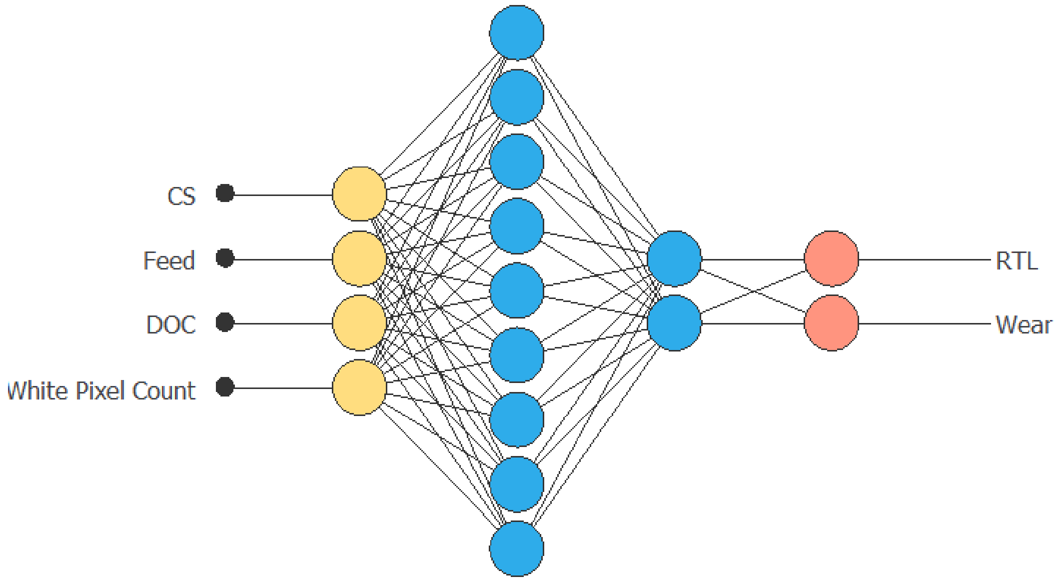


Figure 24 ANN deep architecture

5.3 Training of Data set

The approach utilised to carry out the learning process is known as the training (or learning) technique. To begin, the training is performed using the testing approach to ensure the lowest potential failure rate. This is done by searching for a collection of parameters that will allow the neural network to match the data set.

So Back propagational ANN is mainly known for the reducing the error, and in the training of the dataset, there is the option to choose an error function that is going to reduce the loss. So, in this ANN, there is use of the Mean Squared Error (MSE), which mainly uses in BPNN and the same for improving the results in error with Rectified Linear function (ReLu) there is the use of the Mean squared error. The average squared error between the neural network outputs and the targets in the data set is calculated using the mean squared error.

$$\text{mean\_squared\_error} = \frac{\sum(\text{outputs} - \text{targets})^2}{\text{instances\_number}}$$

Then there is the role of the Regularization term. The loss index specifies the role that the neural network must complete and provides a metric for the consistency of the representation that must be learned. When creating a failure index, you must choose between two terms: an error term and a regularization term. The regularization term calculates the values of the neural network's parameters. When you add it to the error, the neural network's weights and biases reduce, forcing the solution to be cleaner and avoiding overfitting. The L2 regularization approach is used in this instance. It's made up of the squared number of all the neural network's parameters.

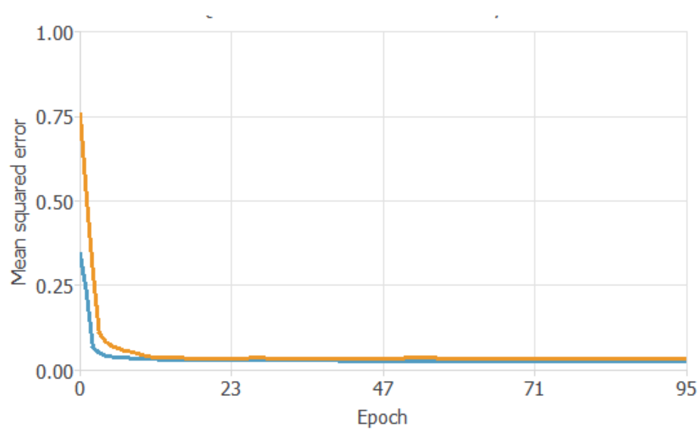


Figure 25 training and selection errors in each iteration

5.4 Model analysis based on Data

Model selection is a technique for determining a neural network's architecture that minimises error on new inputs. Order selection algorithms and input selection algorithms are the two types of model selection algorithms. Order selection methods are used to determine the optimal number of hidden neurons in the network. Input selection algorithms' job is to find the best subset of input variables.

Rising inputs is the input selection algorithm chosen for this program. The inputs are gradually applied using this approach, based on their similarities with the goals. The method of increasing inputs measures the association between each input and each output in the data collection. It determines the selection error for that model by starting with a neural network that only includes the most clustered data. Then, it continues to add the most correlated variables until the selection error grows.

The linear regression for the scaled performance RTL is illustrated in the following graph. As rings, the estimated values are plotted against the actual values. The grey line shows the best linear fit. Some scaled outputs are not plotted because they fall beyond the range specified by the scaled targets.

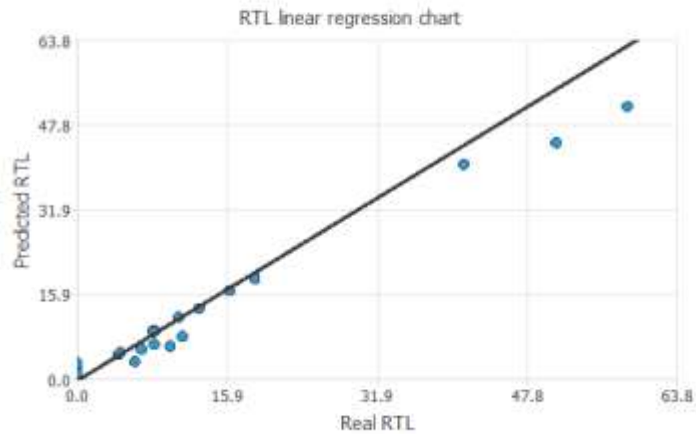


Figure 26 Scaled output RTL Sigmoid Function ANN

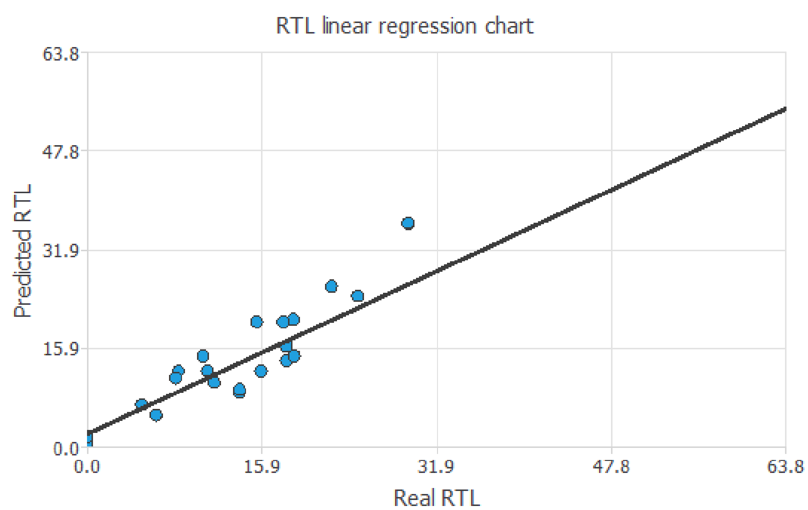


Figure 27 Scaled Output ANN using ReLU

In the same way, the linear regression for scaled performance Wear is shown in the graph below. The estimated values are shown against the true value in the form of circles. The best linear fit is shown by the grey line. Because certain scaled outputs fall beyond the range defined by the scaled objectives, they are not shown.

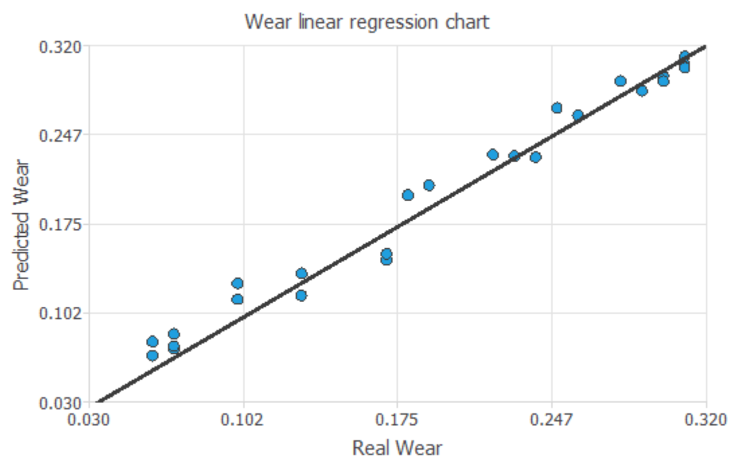


Figure 28 Scaled output wear Sigmoid Function ANN

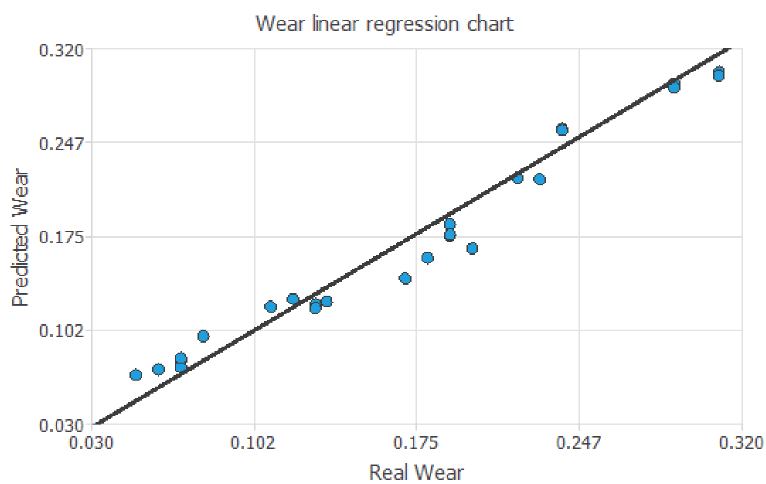


Figure 29 Scaled Output Wear using ReLU

The absolute and percentage errors of the neural network for the testing data for RTL and Wear are shown in the tables below as minimums, maximums, means, and standard deviations.

Table 4 Error table RTL Using Sigmoid Function ANN

	Minimum	Maximum	Mean	Deviation
Absolute error	0.000139	0.025542	0.010818	0.007166
Relative error	0.000479	0.088077	0.037303	0.024711
Percentage error	0.047858	8.80766	3.73026	2.47108

Table 5 Error table wear Using Sigmoid Function ANN

	Minimum	Maximum	Mean	Deviation
Absolute error	0.055241	7.26674	1.65293	1.87232
Relative error	0.000866	0.113968	0.025924	0.029365
Percentage error	0.086637	11.3968	2.59239	2.93647

Table 6 Error Table RTL using ReLU function ANN

	Minimum	Maximum	Mean	Deviation
Absolute error	0.012678	6.80585	2.89943	1.91773
Relative error	0.000199	0.10674	0.045473	0.030077
Percentage error	0.019884	10.674	4.54733	3.00768

Table 7 Error table wear Using Sigmoid Function ReLU

	Minimum	Maximum	Mean	Deviation
Absolute error	4.34E-05	0.035396	0.011981	0.008
Relative error	0.00015	0.122056	0.041314	0.027585
Percentage error	0.014963	12.2056	4.13141	2.75853

So, based on the table Using the Sigmoid function, it shows that output accuracy for the RTL will be 89.61%, and for wear, it will be 92.20%. Based on that, the output samples are shown below. In which it is having the error of 7.77% in RTL and 8.33% with Sigmoid Function ANN.

Table 8 Output table Back Propagational ANN

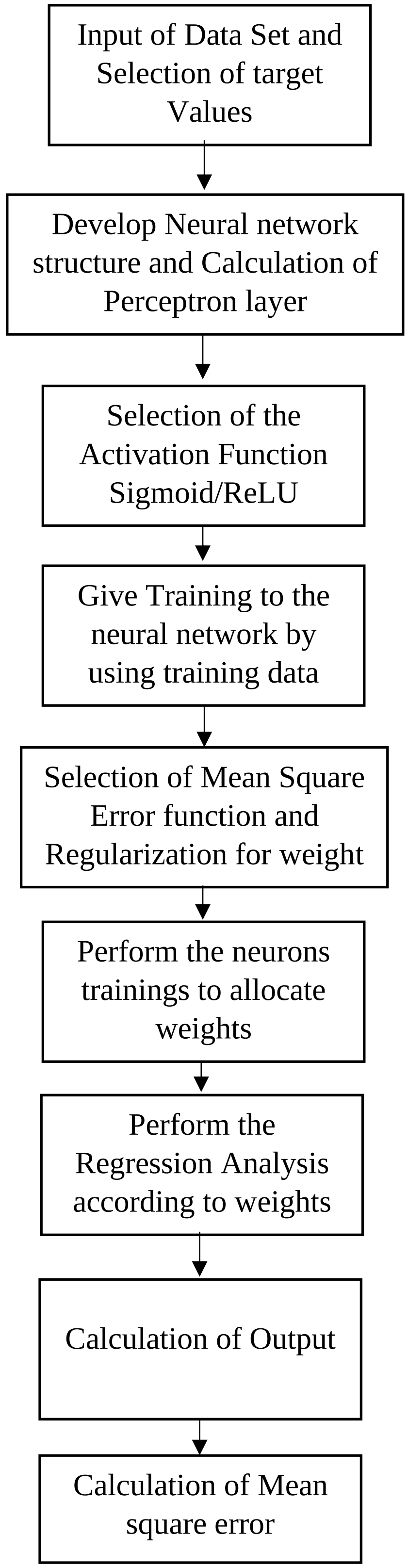
	Value
CS	80
Feed	0.1
DOC	0.4
White Pixel Count	1008
RTL	23.1101
Wear	0.133191

Table 9 Output Table with ReLU function ANN

	Value
CS	80
Feed	0.1
DOC	0.4
White Pixel Count	1008
RTL	24.19564
Wear	0.126375

So, based on the table Using the ReLU function in ANN, it shows that output accuracy for the RTL will be 90.33%, and for wear, it will be 88.80%. Based on that, the output samples are shown below. In which it is having an error of 4.20% in RTL and 5.25% with ReLU function ANN.

5.5 Algorithm for Prediction of Tool life using Sigmoid ANN and ReLU ANN



CHAPTER 6

Results and Discussion

According to the findings of this Project, Artificial intelligence powered models are ideal for two critical tasks related to the automate the task of Tool life and wear prediction in turning operations: image analysis to determine current tool wear and wear prediction based on similar tools in the past. Thus, this thesis presents a two-step approach for the automated prediction of tool life and wear in turning operations that combine these two study lines.

6.1 Discussion of result

In both Back-Propagation ANN and ReLU network ANN Trained with the data collected from the images of the cutting edges and related parameters, then predicted values are predicted based on the experimental data. After that, some image processing techniques applied, giving more accurate results towards the binary image as discussed in the previous chapter. So, the binary image has the area of wear in white pixels with some negligible amount of noise. This wear area varies based on the input parameters like feed, Speed, and depth of cut. So, there are total four inputs feed, Speed, depth of cut and White pixel of image for a neural network. The output is the amount of wear and remaining useful life of the tool. According to the neural network analysis, both outputs are weight changes based on the White pixel of image > Speed > depth of cut > feed comparatively. As a result, the two forms of Network Sigmoid ANN (BPNN) and ReLU ANN, which have two different activation functions and two different algorithms, are used. Both are used in the literature for a more precise prediction of the targeted values. The effect of using both algorithms is shown below, for the same inputs and according to the algorithm accuracy and result shown.

It proves that both are having almost the same accuracy in this data, but ReLU shows more Accuracy in the result in terms of Number and in terms of training time; ReLU takes less time. In Sigmoid function ANN using nine different conditions in Remaining tool life, it shows the 90.87% accuracy, and in wear, it shows the 93.077% of accuracy. On the other hand, the ReLU function using nine different conditions in Remaining tool life shows the 95.27% accuracy and in wear it shows the 92.79% of accuracy, which is more than the Sigmoid Function ANN.

Table 10 Accuracy Table Sigmoid Function ANN

Speed	Feed	DOC	White pixel count	Real RTL	Real Wear	Predicted RTL(BPNN)	Predicted Wear (BPNN)	Accuracy RTL (BPNN)	Accuracy wear (BPNN)
70	0.1	0.3	758	58.53	0.06	51.3	0.07	87.64943	83.33
70	0.15	0.4	1274	13.88	0.19	12.58	0.1928	90.62459	98.53
70	0.2	0.5	1832	0.01	0.28	0.53	0.2895	98.12	96.6
80	0.1	0.4	1197	18.22	0.2	17.58	0.1787	96.49059	89.35
80	0.15	0.5	778	18.88	0.07	19.32	0.0712	97.67	98.31
80	0.2	0.3	1462	5.00	0.22	4.1143	0.218	82.2325	99.09091
90	0.1	0.5	1460	6.85	0.22	5.69	0.23	83.03159	95.98
90	0.15	0.3	734	17.90	0.05	19.21	0.0546	92.689	91.8
90	0.2	0.4	1087	8.10	0.17	8.96	0.144	89.35	84.70588

Table 11Accuarcy table ReLU function ANN

Speed	Feed	DOC	White pixel count	Real RTL	Real Wear	Predicted RTL(ReLU)	Predicted Wear (ReLU)	Error RTL (ReLU)	Error wear (ReLU)
70	0.1	0.3	758	58.53	0.06	53.4241	0.07	91.27859	83.33
70	0.15	0.4	1274	13.88	0.19	12.77	0.1984	91.99332	95.5786
70	0.2	0.5	1832	0.01	0.28	0.4984	0.2857	96.43	97.96
80	0.1	0.4	1197	18.22	0.2	17.91	0.1962	98.30185	98.1
80	0.15	0.5	778	18.88	0.07	19.93	0.06	94.43	85.71429
80	0.2	0.3	1462	5.00	0.22	5.11	0.214	97.86	97.27273
90	0.1	0.5	1460	6.85	0.22	6.94	0.218	98.73	99.09091
90	0.15	0.3	734	17.90	0.05	18.33	0.05213	97.6	95.74
90	0.2	0.4	1087	8.10	0.17	8.84	0.14	90.84	82.35294

6.2 Conclusion

Tool condition monitoring is critical in CNC processes because excessive wear or tool breakage in an automated manufacturing system must be detected quickly in order to preserve efficiency and productivity. Unacceptable tool wear or breakage during metal cutting operations can harm the tool operator, the workpiece, or the machine elements Tool failure will also cause the product's surface quality and dimensional accuracy to deteriorate. Tool breakage may also affect user safety or trigger an issue in the production environment. As a result, instruments must be replaced at the appropriate times.

The primary wear component in this dissertation was flank wear. Because of combined adhesive and abrasive wear processes, the intense rubbing action of the two surfaces in contact, namely the clearance surface of the cutting tool and the freshly formed face of the workpiece, causes flank wear. Its rate of growth is high in the beginning of the tool's life, then settles to a constant level before progressively rising. With this increase of the wear, the area of wear also increases. To detect this, there is the use of the machine vision system, which is shown in chapter 4. Also, it discussed that direct systems are more accurate in chapter 2.

To detect this wear, there is the use of image processing systems which is shown in chapter 4. There is mainly the use of the image enhancement filter, image denoising, and image thresholding, which results in the Binary image with the detection of wear area, which is having one type of pixel. To detect and calculate those pixels, there is use of the algorithm that calculates the pixels of that area. So, this can also be an effective input for the neural network, which is varying with an increase of wear. One of the advantages of using the proposed method is that it is fast and easy to make an effective neural network input. However, for using this method, there is a need for an effective robust illumination system due to the noise on the tool's surface after machining.

After that, there is the use of the ANN models to develop the tool life prediction in which there is the use of the two different functions. The input data was obtained by performing the dry turning operation using the carbide inserts. Details are shown in chapter 3. The significant parameters consider as the input for the data of the Neural network. Finally, there is the development of neural network by using of the Sigmoid and ReLU functions.

6.3 Future Work

In the field of tool life prediction and wear prediction, there is a lot of space for study. The suggested tool life prediction approach can be expanded to include a variety of valuable features.

A mixture of machine vision and neural networks is used in this proposed process. As a result, the data is primarily dependent on machine vision. To achieve a good performance, the Illumination system can be improved to prevent image noise after machining and to provide reliable results.

Here In this dissertation, there is only one kind of material used. However, tool life is also influenced by the material's hardness. As a result, by combining various materials, more data can be produced. This information can be used to create a neural network algorithm that can predict tool life based on material hardness or identity.

Different algorithms and activation functions for neural networks are available depending on the form of prediction. More accurate neural network algorithms can be created to overcome these drawbacks, such as the use of the leaky- relu function in the hidden layer of the back-propagation algorithm.

In this algorithm, the image processing part and neural network part are different. So, to make this process more robust, we can develop an algorithm that allows the neural network algorithm to take input from image processing algorithms directly. So, based on algorithm development, many possibilities are available.

In view of the above, tool life prediction, tool wear prediction, and process automation have many potential. These methods may be helpful to in the development of unmanned devices. Using a combination of artificial intelligence and machine vision to predict tool life and wear will have a faster and more precise performance.

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Appendix

A – Algorithm of Image Processing GUI

```
import tkinter as tk

from tkinter.filedialog import askopenfilename

import processing as pc

from PIL import Image, ImageTk


image_file = None

originimage = None

proceimage = None



def resize(w, h, w_box, h_box, pil_image):

    '''

    resize a pil_image object so it will fit into

    a box of size w_box times h_box, but retain aspect ratio

    '''

    f1 = 1.0 * w_box / w  # 1.0 forces float division in Python2

    f2 = 1.0 * h_box / h

    factor = min([f1, f2])

    # print(f1, f2, factor) # test

    # use best down-sizing filter

    width = int(w * factor)

    height = int(h * factor)

    #resize

    return pil_image.resize((width, height), Image.ANTIALIAS)
```

```
def open_image():
    global image_file

    filepath = askopenfilename()

    image_file = Image.open(filepath)

    w_box = 500
    h_box = 350
    showimg(image_file, imgleft, w_box, h_box)
    showimg(image_file, imgright, w_box, h_box)


def save_image():
    global proceimage
    proceimage.save('images/processed.jpg')


def hst_eql():
    global proceimage
    PIL_eq, PIL_gary = pc.hist_eql(image_file)
    proceimage = PIL_eq

    w_box = 500
    h_box = 350
    showimg(PIL_gary, imgleft, w_box, h_box)
    histO = Image.open('images/templeft.png')
    showimg(histO, histleft, w_box, h_box)
```

```
    showimg(PIL_eq, imgright, w_box, h_box)
    histE = Image.open('images/tempright.png')
    showimg(histE, histright, w_box, h_box)
    # pc.drawHist(PIL_img,'right')
    # draw_hist(PILimg, 'right')


def showimg(PIL_img, master, width, height):
    """
    :param PIL_img:
    :param master:
    :param width:
    :param height:
    :return: nothing
    """

    w, h = PIL_img.size

    img_resize = resize(w, h, width, height, PIL_img)
    # Image 2 ImageTk
    Tk_img = ImageTk.PhotoImage(image=img_resize)
    # master
    master.config(image=Tk_img)
    master.image = Tk_img

def bilateral():
    PIL_detect = pc.bi_lateral(image_file)
```

```
    global proceimage
    proceimage = PIL_detect
    w_box = 500
    h_box = 350
    showimg(image_file, imgleft, w_box, h_box)
    showimg(PIL_detect, imgright, w_box, h_box)
    histleft.config(image=None)
    histleft.image = None
    histright.config(image=None)
    histright.image = None

def edge():
    PIL_detect = pc.edge_detect(image_file)
    global proceimage
    proceimage = PIL_detect
    w_box = 500
    h_box = 350
    showimg(image_file, imgleft, w_box, h_box)
    showimg(PIL_detect, imgright, w_box, h_box)
    histleft.config(image=None)
    histleft.image = None
    histright.config(image=None)
    histright.image = None

def Otsu():
    global proceimage
    PIL_gary,PIL_Otsu = pc.Otus_hold(image_file)
    proceimage = PIL_Otsu
```

```
    w_box = 500
    h_box = 350
    showimg(PIL_gary, imgleft, w_box, h_box)
    showimg(PIL_Otsu, imgright, w_box, h_box)
    histleft.config(image=None)
    histleft.image = None
    histright.config(image=None)
    histright.image = None




root = tk.Tk()
root.title('Image Processing GUI')
root.geometry('1100x700')
root.config(bg='white')

# Menu
menubar = tk.Menu(root)
filemenu = tk.Menu(menubar, tearoff=0)
filemenu.add_command(label='Open', command=open_image)
filemenu.add_command(label='Save', command=save_image)
operate = tk.Menu(menubar, tearoff=0)
operate.add_command(label='Histogram eql', command=hst_eql)
operate.add_command(label='Edging', command=edge)
operate.add_command(label='OTSU',command=Otsu)
menubar.add_cascade(label='File', menu=filemenu)
menubar.add_cascade(label='Process', menu=operate)
```

```
# window frame
frm = tk.Frame(root, bg='white')
frm.pack()
#frame
frm_left = tk.Frame(frm, bg='white')
frm_right = tk.Frame(frm, bg='white')
frm_left.pack(side='left')
frm_right.pack(side='right')

imgleft = tk.Label(frm_left, bg='white')
histleft = tk.Label(frm_left, bg='white')

imgright = tk.Label(frm_right, bg='white')
histright = tk.Label(frm_right, bg='white')
imgleft.pack()
histleft.pack()
imgright.pack()
histright.pack()
# canvasl = tk.Canvas(frm_left, bg='white').pack()
# canvasr = tk.Canvas(frm_right, bg='white').pack()


root.config(menu=menubar)
root.mainloop()
```

B – Wear area Calculation in Binary image

```
import extcolors

import PIL

img = PIL.Image.open("processed.jpg")

colors, pixel_count = extcolors.extract_from_image(img)

color_count = sum([color[1] for color in colors])

for color in colors:

    rgb = str(color[0])

    count = color[1]

    percentage = "{:.2f}".format((float(count) / float(color_count)) * 100.0)

    print(f"{rgb:15}:{percentage:>7}% ({count})")


print(f"\nPixels in output: {color_count} of {pixel_count}")

print(colors)
```

C – Model of ReLU function based ANN

Generated by Neural designer

```
import numpy as np


def scaling_layer(inputs):


	outputs = [None] * 4


	outputs[0] = inputs[0]*0.1000000015-8
	outputs[1] = inputs[1]*20-3
	outputs[2] = inputs[2]*10.00000095-4
	outputs[3] = inputs[3]*0.00127469725-1.632249832


	return outputs;



def perceptron_layer_0(inputs):


	combinations = [None] * 11


	combinations[0] = 0.537486 -0.00788238*inputs[0] -0.00165123*inputs[1] +0.00956782*inputs[2] +0.817742*inputs[3]
	combinations[1] = -6.88798e-07 +3.34307e-06*inputs[0] +4.32348e-07*inputs[1] +1.91638e-07*inputs[2] +1.19681e-05*inputs[3]
	combinations[2] = -3.08871e-08 -9.33169e-07*inputs[0] -8.546e-08*inputs[1] -1.84093e-06*inputs[2] -2.32943e-07*inputs[3]
	combinations[3] = -4.46989e-06 -1.569e-06*inputs[0] +2.18369e-06*inputs[1] +1.15098e-06*inputs[2] -0.70029*inputs[3]
	combinations[4] = -6.87978e-05 -5.84881e-07*inputs[0] +6.08543e-07*inputs[1] +2.3963e-06*inputs[2] +1.50531e-06*inputs[3]
```

combinations[5] = 2.1308e-06 +3.19853e-07*inputs[0] -7.37305e-07*inputs[1] +2.11686e-07*inputs[2] +2.44475e-07*inputs[3]

combinations[6] = -0.236449 -0.200143*inputs[0] -0.299124*inputs[1] -0.146571*inputs[2] -0.581935*inputs[3]

combinations[7] = -5.63112e-06 +1.49265e-06*inputs[0] +2.73941e-06*inputs[1] +1.47329e-06*inputs[2] -7.3631e-07*inputs[3]

combinations[8] = -7.80177e-07 -2.2044e-06*inputs[0] -6.85026e-08*inputs[1] -3.84152e-07*inputs[2] -2.24839e-07*inputs[3]

combinations[9] = -7.03071e-07 -4.23363e-07*inputs[0] -1.15545e-05*inputs[1] +2.74303e-06*inputs[2] -9.58471e-06*inputs[3]

combinations[10] = -2.44244e-07 +1.7465e-07*inputs[0] -2.60753e-07*inputs[1] -4.931e-06*inputs[2] +1.79774e-07*inputs[3]

activations = [None] * 11

activations[0] = np.maximum(0.0, combinations[0])

activations[1] = np.maximum(0.0, combinations[1])

activations[2] = np.maximum(0.0, combinations[2])

activations[3] = np.maximum(0.0, combinations[3])

activations[4] = np.maximum(0.0, combinations[4])

activations[5] = np.maximum(0.0, combinations[5])

activations[6] = np.maximum(0.0, combinations[6])

activations[7] = np.maximum(0.0, combinations[7])

activations[8] = np.maximum(0.0, combinations[8])

activations[9] = np.maximum(0.0, combinations[9])

activations[10] = np.maximum(0.0, combinations[10])

return activations;

```
def perceptron_layer_1(inputs):

	combinations = [None] * 2

	combinations[0] = -0.53546 -0.354458*inputs[0] +6.51959e-07*inputs[1] -1.47839e-06*inputs[2] -8.98759e-06*inputs[3] +1.03627e-06*inputs[4] -4.10028e-06*inputs[5] +1.45207*inputs[6] -1.12607e-06*inputs[7] -4.7916e-06*inputs[8] -5.01284e-07*inputs[9] -1.66629e-06*inputs[10]
	combinations[1] = -0.41537 +1.02279*inputs[0] -4.96662e-06*inputs[1] +5.39511e-07*inputs[2] -0.6701*inputs[3] +5.48958e-06*inputs[4] -4.91563e-06*inputs[5] -1.54373e-05*inputs[6] -6.34868e-06*inputs[7] -4.90378e-06*inputs[8] -7.37416e-06*inputs[9] -5.47894e-06*inputs[10]

	activations = [None] * 2

	activations[0] = combinations[0]
	activations[1] = combinations[1]

	return activations;


def unscaling_layer(inputs):

	outputs = [None] * 2

	outputs[0] = inputs[0]*31.88055038+31.88055038
	outputs[1] = inputs[1]*0.1449999958+0.174999997

	return outputs
```

```
def bounding_layer(inputs):

	outputs = [None] * 2

	outputs[0] = inputs[0]
	outputs[1] = inputs[1]

	return outputs


def neural_network(inputs):

	outputs = [None] * len(inputs)

	outputs = scaling_layer(inputs)
	outputs = perceptron_layer_0(outputs)
	outputs = perceptron_layer_1(outputs)
	outputs = unscaling_layer(outputs)
	outputs = bounding_layer(outputs)

	return outputs;
```

D - Model of Sigmoid function-based ANN

Generated by Neural designer

```
import numpy as np


def scaling_layer(inputs):


	outputs = [None] * 4


	outputs[0] = inputs[0]*0.1000000015-8
	outputs[1] = inputs[1]*20-3
	outputs[2] = inputs[2]*10.00000095-4
	outputs[3] = inputs[3]*0.00127469725-1.632249832


	return outputs;



def perceptron_layer_0(inputs):


	combinations = [None] * 13


	combinations[0] = 0.00507455 +0.0672776*inputs[0] +0.0467513*inputs[1] -0.00824611*inputs[2] +0.161761*inputs[3]
	combinations[1] = 0.0229344 +0.000227565*inputs[0] -0.0453629*inputs[1] +0.0144833*inputs[2] -0.167046*inputs[3]
	combinations[2] = -0.10902 +0.0764405*inputs[0] -0.192605*inputs[1] +0.0817081*inputs[2] -0.358114*inputs[3]
	combinations[3] = 0.000308434 +0.0434981*inputs[0] +0.0247044*inputs[1] -0.006747*inputs[2] +0.0960661*inputs[3]
	combinations[4] = 0.839693 +0.259*inputs[0] +0.386539*inputs[1] +0.18133*inputs[2] +0.461899*inputs[3]
```

```
combinations[5] = -0.19776 -0.311502*inputs[0] +0.370101*inputs[1] -0.145899*inputs[2] +0.313221*inputs[3]

combinations[6] = 0.16305 -0.24226*inputs[0] -0.422396*inputs[1] -0.567468*inputs[2] -0.542834*inputs[3]

combinations[7] = -0.25014 -0.0486417*inputs[0] -0.353556*inputs[1] +0.182743*inputs[2] +0.591619*inputs[3]

combinations[8] = 0.155828 -0.355114*inputs[0] -0.255711*inputs[1] -0.454102*inputs[2] +0.62185*inputs[3]

combinations[9] = -0.574642 -0.0349842*inputs[0] -0.0145176*inputs[1] -0.0389507*inputs[2] -1.03432*inputs[3]

combinations[10] = -0.0230541 +0.0169187*inputs[0] +0.0861011*inputs[1] -0.0271967*inputs[2] +0.153126*inputs[3]

combinations[11] = 0.0221035 -0.0712259*inputs[0] -0.0726223*inputs[1] +0.0350106*inputs[2] -0.200663*inputs[3]

combinations[12] = 0.0214245 -0.0346281*inputs[0] -0.0594963*inputs[1] +0.0126227*inputs[2] -0.15331*inputs[3]


activations = [None] * 13


activations[0] = np.tanh(combinations[0])

activations[1] = np.tanh(combinations[1])

activations[2] = np.tanh(combinations[2])

activations[3] = np.tanh(combinations[3])

activations[4] = np.tanh(combinations[4])

activations[5] = np.tanh(combinations[5])

activations[6] = np.tanh(combinations[6])

activations[7] = np.tanh(combinations[7])

activations[8] = np.tanh(combinations[8])

activations[9] = np.tanh(combinations[9])

activations[10] = np.tanh(combinations[10])

activations[11] = np.tanh(combinations[11])
```

```
    activations[12] = np.tanh(combinations[12])

    return activations;


def perceptron_layer_1(inputs):

    combinations = [None] * 2

    combinations[0] = -0.10927 -0.171345*inputs[0] +0.109978*inputs[1] +0.303299*inputs[2] -0.105012*inputs[3] -0.917641*inputs[4] -0.409989*inputs[5] -0.686972*inputs[6] -0.63238*inputs[7] +0.675356*inputs[8] +0.295727*inputs[9] -0.100509*inputs[10] +0.191514*inputs[11] +0.136318*inputs[12]
    combinations[1] = -0.237005 +0.0797261*inputs[0] -0.127937*inputs[1] -0.310038*inputs[2] +0.0701027*inputs[3] -0.139763*inputs[4] -0.0876597*inputs[5] -0.154764*inputs[6] +0.298455*inputs[7] +0.198689*inputs[8] -0.89561*inputs[9] +0.118346*inputs[10] -0.138083*inputs[11] -0.129516*inputs[12]

    activations = [None] * 2

    activations[0] = combinations[0]
    activations[1] = combinations[1]

    return activations;


def unscaling_layer(inputs):

    outputs = [None] * 2
```

```
	outputs[0] = inputs[0]*31.88055038+31.88055038
	outputs[1] = inputs[1]*0.1449999958+0.174999997

	return outputs


def bounding_layer(inputs):

	outputs = [None] * 2

	outputs[0] = inputs[0]
	outputs[1] = inputs[1]

	return outputs


def neural_network(inputs):

	outputs = [None] * len(inputs)

	outputs = scaling_layer(inputs)
	outputs = perceptron_layer_0(outputs)
	outputs = perceptron_layer_1(outputs)
	outputs = unscaling_layer(outputs)
	outputs = bounding_layer(outputs)

	return outputs;
```

Report revised

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