Redefining the tool condition monitoring: A framework for machining quality prediction and tool life management

by

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ABSTRACT

Tool wear morphology is one of the established topics in the field of manufacturing. Wear morphology monitoring offers significant information about the machining process such as, the condition of the tool and the quality of the machined component, but the information has not been utilized to its full potential in the automation of the machining processes. The objective of the thesis is to proposes different systems that utilize this tool wear morphology information for tool condition monitoring (TCM), machining quality improvement, and machining parameter optimization. The proposed study has four objectives. First, the development of a new definition for TCM considering the barriers between present TCM systems and their deployment in machine shops around the world. Second, the development of a TCM system that achieves the proposed new definition of TCM. Third, the development of a fuzzy controller that helps in machining parameters optimization decision making with the objective of tool life improvement utilizing the wear morphology information as feedback. Lastly, a TCM methodology for monitoring form tools that develop wear on different tool surfaces is proposed. Monitoring the wear morphologies also helps the developed systems to work with different, workpiece materials, tool geometries and tool grades; this allows a faster transition of the proposed systems to industrial setups. The proposed systems use advanced artificial intelligence technologies life Convolution Neural Network, Transfer Learning, and Fuzzy logic to achieve the objectives.

PREFACE

The work presented is an original study conducted by Harshavardhan Mamledesai. The study has produced two journal papers and one conference paper. Therefore, the thesis is organized in the paper format following paper-based thesis guidelines. Following are the research articles published or in process of submission.

1. **Harshavardhan Mamledesai**; Mario A. Soriano; Rafiq, Ahmad. A Qualitative Tool Condition Monitoring Framework Using Convolution Neural Network and Transfer Learning. *Appl. Sci.* **2020**, *10*, 7298. DOI: https://doi.org/10.3390/app10207298
2. **Harshavardhan Mamledesai,** Yufan Zheng, Rafiq, Ahmad, Improving tool life by optimizing machining parameters: Using autonomous fuzzy logic controller and image data 2020, SN Applied Sciences (Submitted)
3. **Harshavardhan Mamledesai,** Rafiq, Ahmad, Tool condition monitoring method for threading and grooving tools 2020, 10th CIRP Sponsored Conference on Digital Enterprise Technologies (DET 2020) – Digital Technologies as Enablers of Industrial Competitiveness and Sustainability. (Submitted)

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Contents

List of tables

List of figures

Chapter 1: Introduction

The age of industrial automation is also an age of many theories. Although these theories are different, there are, however, many overlapping objectives. Value stream mapping (VSM) talks about non-value adding activities (NVA), necessary but non-value-adding activities (NNVA), and value-adding activities (VA) [1]. Similarly, "lights out machining" (LOM) is the utopian concept of eliminating all human intervention activities in machine shops [2]. Zero defect manufacturing (ZDM) talks about reducing the number of defected parts to zero [3]. But to eliminate all the non-value adding activities, supervision, and the production of defective parts, a reliable data source that is obtained in time is essential. Tool condition monitoring can be this reliable data source that is obtained at the in time to achieve the elimination of non-value adding activities for VSM, elimination of supervision for LOM, and preventing the production of defective parts for ZDM. In the rest of this chapter, the background of different non-value adding activities addressed by this thesis is discussed. Finally, the objectives of the proposed study are discussed in Section 1.6.

1.1 Background

The world is in the cusp of the fourth industrial revolution, which is commonly known as "Industry 4.0." This industrial revolution has pushed for more autonomous and intelligent manufacturing setups around the world. The objective of the push towards autonomous machines is to prepare the machines for operations without the intervention of human operators, which is also known as "lights out machining" [4]. This transition towards lights out machining presents the opportunity to develop algorithms and frameworks to do the work traditionally expected from the Computerized Numerical Control (CNC) machine operators. Traditional responsibilities of an operator included TCM, tool replacement, optimization of machining parameters for better tool life, and looking out for quality deviation of the manufacturing processes. The motivation of the study is to provide frameworks and intelligent algorithms that can replicate the human operator decision making in performing the tasks mentioned above. The autonomous solutions not only provide an alternative for human intelligence but also provide the prediction capabilities. The prediction capabilities help in two ways:

1) Improving the tool life, which can account for up to 12 percent of production cost [5].
2) It helps in the prevention of using wrong tools that result in the production of non-conforming parts before they are produced. The prediction capabilities help save the tooling overheads, raw material cost, and other resources that might have been wasted in the production of these non-conforming components.

Thus, the replication of human decision making for lights out machining and the advantages of predicting machining outcomes in machine shops around the world form the underpinning motivations for the study.

1.2 Tool condition monitoring (TCM)

TCM is one of the extensively studied fields in the past decades, and over the years, many indirect and direct monitoring techniques have been developed [6]. Indirect monitoring systems are real-time systems that give feedback on the change in tool behavior, and these changes are correlated to the definition of tool condition. There are different methods within indirect methodologies, acoustic[7], force [8], vibration [8–10], to name a few. On the other front, direct methods rely on visual evidence [11] of the tool, which limits the scope of making direct systems the real-time systems, which means TCM can not take place while the machining operation is in progress. The direct systems, however, are less prone to noise [12], which is a barrier for indirect monitoring for the full deployment in machine shops around the world. The direct systems frameworks, on the other hand, can be developed to work between machining cycles [13] when the tool is not in use. Thus, taking advantage of accurate measurements while making the systems in-process and impervious to different noise signals ordinarily present in the machine shops.

While there are many works of literature on monitoring the tools and their applications, it is worth noting that there is no single definition for the tool condition. Some studies use TCM for the detection of defects in the tools [14], TCM is also used as a prediction tool to predict the tool life [15], others consider TCM as the quantification of wear on the cutting tool [16], and very few studies correlate TCM with machining quality. This lack of a formal definition has resulted in systems that work in ideal lab conditions but fail to work in real-world machine shops. The thesis, therefore, proposes a new definition of TCM. TCM, according to the new proposed definition, has two objectives. One is to define a good tool that produces a component that meets the design requirement (conforming parts) and a bad tool that produces a component that does not meet the design requirements (non-conforming parts). Second, TCM detects the transaction of a tool from good to bad and the threshold between them. The detection allows the system to warn the machine or the machinist to prevent the production of non-conforming parts.

This versatile definition of the TCM presents another challenge of generalization. The component can be classified as non-conforming because of a variety of reasons or defects. Therefore, the TCM systems must be capable of generalizing and working with a variety of quality and functional requirements.

1.3 Quality management in machine shops around the world

Quality management in industries around the world has moved towards a qualitative approach with the application of GO / NO GO gauges. GO / NO GO gauges are traditionally used to manage material conditions in holes and shafts [17]. GO gauges are designed to accept all possible tolerances that meet the design requirements, while NO GO gauges are designed to reject all possible tolerances that don't meet the design requirements [17]. This concept gives the quality management in a machine shop floor two advantages. One, it makes quality management faster as the quality engineer doesn't have to measure the quantity of the deviation from the base specification. Second, it is easier to teach the operators to manage the quality as it requires no expert skills or knowledge, and the skills and knowledge that are necessary can be easily taught to anyone with no knowledge prerequisites.

GO / NO GO gauges have inspired the development of our frameworks for TCM using artificial intelligence. GO / NO GO approach allows the developed system to be qualitative, which is accept or reject the component rather than quantitative. The quantitative approach has been taken by most of the studies [15, 16, 18, 19]. The quantitative method also forms one of the barriers to the deployment of TCM in machine shops around the world, discussed later in Section 2.4. GO / NO GO concept used in the developed framework also allows the system to be flexible so that it can be generalized for different quality and functional requirements. GO /NO GO approach also makes the framework more proactive in dealing with quality management. Therefore ideally, the TCM framework developed rejects the use of all tools that produce a component that does not meet the design requirements, and also, allow the use of all tools that produce a part that matches the design requirements.

1.4 Machining parameters optimization

Cutting speed, feed rate and depth of cut are the three most important parameters of metal cutting. The combination of these three parameters have an effect on various facets of machining, for example, surface finish [20–25], power consumption [24], production time [26], material removal rate [27] among others. Therefore, the optimization of the above-mentioned parameters has attracted many studies, and since the parameters affect various aspects of machining, the objective of optimization has also been different. Tool life is one of such objectives for machining parameter optimization.

Generalization is one of the biggest challenges in the context of machining parameter optimization. Most of the studies are experiment-based systems; in these systems, many different parameter combinations are tried, and the best objective is chosen for the concerned objective. Experiment based systems have their constraints when there is need for generalization. Changing one or more aspects of the experiment renders the results of the experiment unusable in the new setup. The machines shops around the world have different applications and working materials. Therefore, the experimentation approach is not the best when it comes to the deployment of parameter optimization systems.

Machining parameter optimization with tool life as objective and with the aid of TCM is one of the least explored fields of machining parameter optimization. In tool wear, there are desired and undesired wear patterns [28]. The desired wear patterns must persist for the full utilization of tool life. TCM techniques can be repurposed for the detection of undesired wear patterns and suggest the remedy for optimization of machining parameters for the full utilization of the tool life. Since the optimization is based on the evidence of tool wear mechanisms, these frameworks provide a higher degree of flexibility, to accommodate different workpiece materials, and for deployment in machine shops around the world.

1.5 TCM for form tools

TCM in form tools like thread cutting tools needs a different approach than an approach taken for a single-point cutting tool. The V-shape wear pattern is one of the commonly seen wear patterns in forming tools [29] since these tools take a higher depth of cut and feed rates, different faces and nose of the tools come in contact with the workpiece as compared to only nose contact in single-point cutting tools. Therefore, the system for TCM with respect to form tools need a three-dimensional description of the cutting edge. The three-dimensional description allows for the inspection of all the faces of the tool. The three-dimensional approach also improves TCM in a single-point cutting tool as it presents the opportunity of monitoring different rake angles.

1.6 Research objectives

The research objectives are derived from the deployment barriers and gaps identified in the field of TCM and its applications. TCM used to achieve different objectives is the theme of the presented thesis. The main objectives are listed and briefly summarized in Fig. 1.1 and the following points.

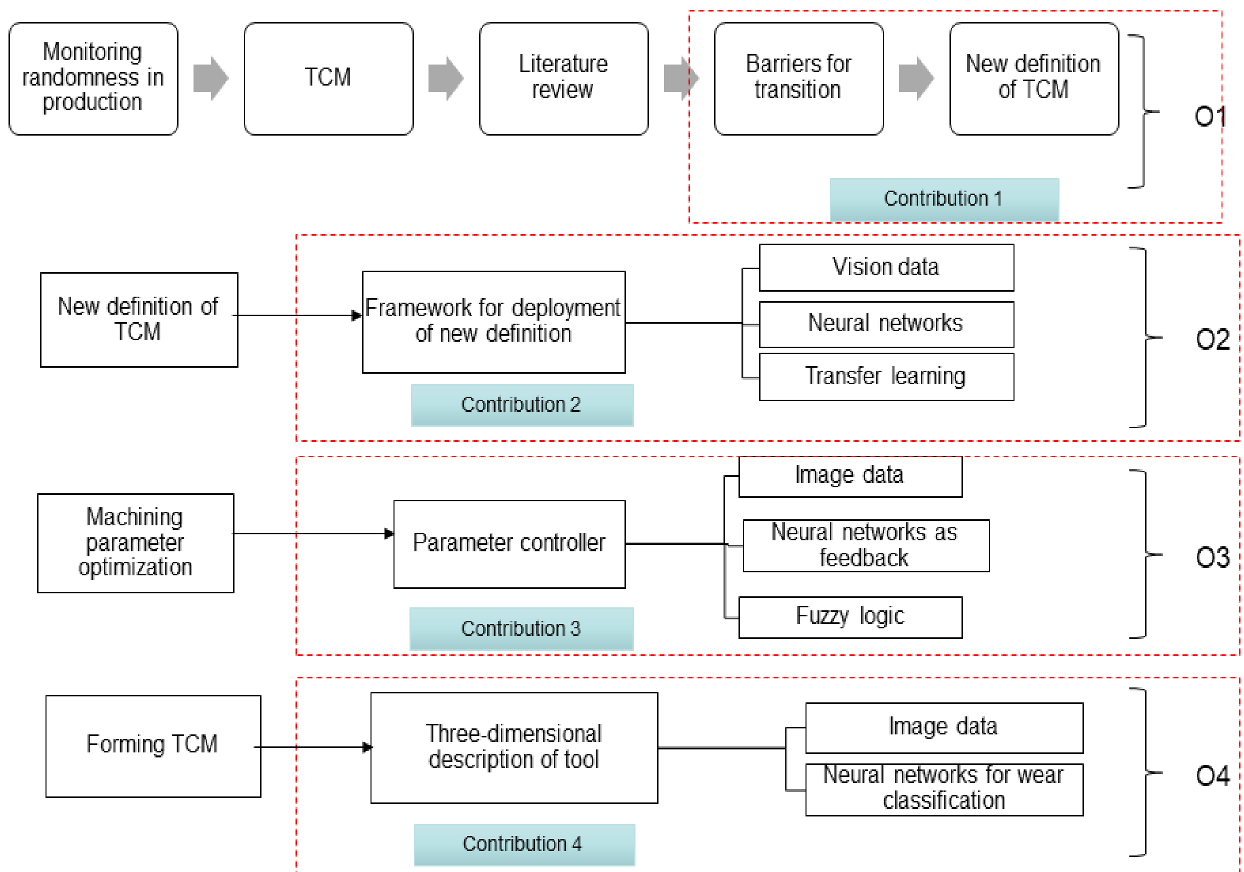


Fig. 1.1 Research objectives and contributions

1. Understand the barriers to deployment of TCM in the industry. Despite a variety of technologies, TCM has failed to transition from a laboratory setup to an industrial setup. The first objective is to understand the reasons for these failures and to develop a new definition for TCM that can overcome these barriers.
2. Develop a framework to implement the new definition. This software framework must be ready for deployment.
3. Develop a machining parameter optimization controller. This controller must be able to accommodate the changes in workpiece material, tool geometry, and tool coating grades.
4. Develop a TCM framework for forming tools such as threading and grooving tools that take heavy depth of cuts. This framework must be able to work with different nose radius and shapes of forming tools.

Chapter 2: Barriers to the translation of TCM from laboratory to machine-shops

TCM is one of the standard topics for research and development in manufacturing, which has been explored for the last four decades. The advancement in TCM has failed to translate from a laboratory setting to an industrial setting. In this chapter, the reasons and barriers for this translation are explored. Before discussing the barriers, the study discusses the advancement in TCM, types of TCM technologies, and the preconceived notions concerning types of TCM and how these notions are challenged with the advancement in technologies. Finally, the study proposes a new definition for TCM that helps bridge the gaps between existing TCM systems and TCM systems that can be deployed in machine shops around the world. The following topics are summarized based on studies listed in Annexure a.

2.1 Importance of tool condition monitoring

The world of manufacturing is undergoing a technological transformation of Industry 4.0. One of the objectives of this technological transformation is to make manufacturing more autonomous [30] to achieve the concept of "lights out machining." Lights out machining refer to making manufacturing facilities run without the need for human operations, and the monitoring can be done remotely [2, 31] to change the processes if necessary. TCM is one of the significant challenges in the realization of these autonomous and remotely manageable manufacturing systems.

TCM is one of the classical problems in the field of mechanical engineering, solutions to which are being developed since 1980 [5]. TCM is traditionally is the responsibility of the machine operator [32]. Machining operations rely on the expert knowledge of the machine operator to monitor the tool condition [33], and based on that knowledge, tools are changed as and when required. The primary objective of TCM is to replace this human intervention to achieve the lights out machining concepts. In the case of high precision machining where the tolerances are tight, and the cost of rejection is high, the human expert judgment can not be relied upon [32]. Therefore TCM is critical is developing tool changing policies [34] that can be autonomously executed without the need for human intervention.

Apart from the autonomous machining systems, the condition of the tool also affects other manufacturing aspects; as much as 20 percent of the machine downtime is attributed to machine tools; machine tools also contribute up to 12 percent to machining cost [5]. Tool condition also affects geometrical and dimensional features of the component being machined [35]. The use of a tool in bad condition contributes to loss of time invested in the preprocessing of the part leading up to the machining, raw material, and human resource, invested in the component [36]. Full utilization of tool life is another problem addressed by TCM. Underutilization of cutting tools is a problem in machine shops around the world due to the conservative approach machine operators take towards tool life to prevent rejection of components; in some cases, the tool can be used only for 50 percent of its life [37]. Considering the points mentioned above, a proactive TCM system can potentially reduce the machine downtime, reduce the machining cost, reduce the rejection of machined parts by monitoring the quality and help in full utilization of tool life.

As discussed in Section 1.2, TCM system can be classified into direct and indirect systems. Both the direct and indirect technologies developed to date have failed to translate their success from laboratory setups to industrial setups. The first objective is aimed to understand the existing systems and identify the barriers that block the translation. The rest of the chapter is organized as follows. Section 2.2 discusses the indirect systems and technologies which are summarized at the end of the section. Section 2.3 addresses the direct technologies followed by the summary of the direct technologies. Finally, in Section 2.4, a new definition for TCM is proposed that helps the TCM technologies make the transition from laboratory settings to industrial settings.

2.2 Indirect methods

Indirect methods are classified as online systems considering that they don't need the tool to be disassembled from the machine to conduct the tool inspection; instead, the signals generated during the machining are captured and analyzed [35]. Indirect methods can also be classified as non-invasive methods [38]. In this section, different indirect signal acquisition methods are discussed, and at the end of the section, various advantages, disadvantages of indirect systems are discussed.

2.2.1 Force signals

Force signals are the most popular signals analyzed when it comes to indirect systems [13]. For the cutting of metal to take place, some force is exerted by the cutting tool on the workpiece. As the cutting tool gets used, the cutting edge loses is sharpness, which results in more cutting force required to perform the same cutting action [5]. This forms the basis of force-sensing technology. Usually, a dynamometer is placed near the to where the cutting is taking place to measure the force [39, 40]. Modern CNC machines also have the cutting load on the machine displayed on the machine console. Machine operators have relied on this load gauge to determine the condition of the tool.

Wang et al. [41] developed a system that has a dynamometer installed on the work clamping device, and the force signals are detected and recorded at the same time the tool is classified into different levels of wear using an optical microscope. The force signals are then correlated with corresponding wear patterns. Liu and Jolley [39] developed a system to acquire tangentially, radial, and longitudinal force, using a dynamometer near the cutting operation at the same time the tool wear level was measured offline. As illustrated by the two studies, force-based TCM technologies require the installation of sensing devices close to the cutting operations, which is unfeasible in practical applications where the machine handles a variety of workpieces.

The force-based systems are also challenging to generalize across different materials and tool geometries. As the models have to be retrained for different tool geometries and materials as the force exerted by roughing tools is higher when compared to force exerted by finishing tools. Similarly, the force required to cut a cast iron material is different when compared to the aluminum component. The changes in tool geometry or the working material render the optimized models of the studies unusable.

2.2.2 Vibration signals

The cutting action generates vibrations in the machine tool due to the effort put by the machine on the tool [35]. As the conditions deteriorate, the behavior of these signals changes, vibration-based systems rely on the detection of this change in behavior. Vibration-based systems use an accelerometer placed on the spindle [42, 43]. The signals from the accelerometer are then preprocessed before useful features are extracted to develop descriptions of the tool conditions. At the same time, the tool condition is measured and classified into different levels of wear using a microscope [43].

Vibration-based systems are better off when compared to force sensor-based systems as they do not need sophisticated sensors close to workpiece or cutting action. However, the vibration-based system suffers from generalization problems too. The vibration signals generated to develop the prediction models are generated using one machining parameter [42] when these machining parameters like feed rate, depth of cut, cutting speed, and tool engagement are changed, the assumption renders the model unusable. The vibrations on the machine tool are also influenced by the stability and rigidity of the machine tool makers. Considering the different machining parameters and machine tools makers, vibration-based TCM is not the best approach when generalization for deployment in real machine shops around the world.

2.2.3 Acoustic emission sensing

Ravindra et al. [44] define acoustic emission as a transient elastic wave generated by the rapid release of energy from a localized source or source within a material when subjected to a state of stress. These acoustic signals change with the change in the internal structure of the material; this forms the basis of the concept of acoustic emission sensing based systems. When the cutting tool geometry changes due to plastic changes in the tool, the acoustic signal behavior changes. Typically a microphone is placed close to the cutting operation to detect these signals. The useful features that give the tool condition descriptions are then extracted from the acoustic signals.

The cutting tool itself has five sources of acoustic emission, plastic deformation in the primary shear zone, plastic deformation in the secondary shear zone, friction due to sliding contact, chip fracture, and sliding contact between the work surface and the tool flank face [7]. When these systems are deployed in the machine shops, they also have to deal with the environmental noise generally found in busy machine shops, and this limits the use of this technology in real-world machine shops. The system also requires sensors close to the metal cutting, which constraints the size of the workpiece [45]. The predictive models in acoustic sensing based systems have to be retrained for different tool geometries as different tool geometries behave differently when generating acoustic signals.

2.2.4 Sensor and data fusion

The complexity of the machining process means that no one indirect sensory feature can adequately describe the tool condition [46]. Setiawar et al. [31] combined signals from an accelerometer, temperature sensor, and power consumption monitoring device, to develop descriptions of tool condition. Jemielniak et al. [47] used five domains extracted from acoustic emission sensors, accelerometer, and force sensors to develop tool condition information, and the study also pointed to the difficulty in determining which domain has the best description while the signals are being acquired. Massol et al. and Geramifard et al. [45, 48], both developed systems that relied on sensory information from the accelerometer, acoustic emission, dynamometer to develop tool condition description. All the sensor fusion-based technologies require an additional step of selecting the right domain and sensor for tool description; this adds to the complexity of an already intricate system. The sensor fusion-based systems also require sensors that are close to the cutting operations, which is not feasible for deployment in machine shops as the machines are expected to machine components of different sizes and shapes.

2.2.5 Indirect systems summary

Indirect systems are online systems, which rely on the passive signals generated during the cutting action. The literature review concerning indirect systems revealed the following takeaways,

- No one signal is capable of developing a tool condition description.
- The systems are sensitive towards the proximity of sensors to the cutting actions. Therefore, they need sensors close to the cutting action.
- The systems are prone to noise, which limits their practical deployment in machine shops.
- The CNC machines require to handle different sizes and shapes of workpieces, the proximity of the sensors close to cutting action limit the size of the workpiece.

- There is an added step of feature extraction in indirect systems, and another added step of feature selection in sensor fusion based indirect systems.
- Generalization is not addressed in any of the studies, when the tool geometry, the working material or the quality requirement change, the models have to be retrained.
- Most of the studies concentrate on developing systems to quantify the tool condition, usually in terms of millimeters of flank wear, while TCM in machine shops is qualitative.
- There is a need for the development of TCM systems that can accommodate and execute different tool change policies depending on the design and quality requirements.

2.3 Direct systems

Direct systems rely on the detection of physical changes on the tool to develop tool condition descriptions instead of passive signals from cutting, which makes them more accurate in comparison to indirect systems [13]. Detection of physical changes also means the data acquisition cannot happen while the cutting action is in the process; this is why the direct systems are called offline systems. However, the offline nature of direct systems is not a crippling disadvantage, as presented by most of the indirect system literature. The TCM is predictive, and the machinist is interested to know if the tool is used weather it produces a conforming part or a non-conforming part. In other words, the machinist has a tool change policy in mind, which prevents him, from using a tool that produces a non-conforming part. The direct systems can be developed to work between cycles [13] to develop and implement these tool change policies autonomously and independently while taking advantage of their higher accuracy and ability to be impervious to different noises. Considering the advantages of higher accuracy, ability to be unaffected by environmental noise, and ability to proactively work in between cycles to predict the consequence of using the tool, direct methods are the most suitable systems for deployment of TCM systems in machine shops around the world.

The direct methods are broadly classified into three categories, optical-based systems, radiation-based systems, and resistance-based systems [13]. Optical-based systems rely on the image sensors to capture the images of the cutting tools. Radiation based systems the cutting edge surface of the tools are made radioactive, and the presence of radioactivity is measured to determine the tool condition [49]. The radiation-based systems, while were accurate they were also hazardous and costly systems due to which these systems lost popularity in the early 90s. For the cutting to take place, three rules must be followed; 1) there must be relative motion; 2) the metal being cut must be softer than the cutting tool; 3) the tool must have the wedge shape or must be sharp. When the sharpness of the tool is reduced, the contact area between the tool and the workpiece increases, and the resistance for the electric flow decreases, resistance-based systems detect this change in resistance to determine the tool condition [13]. Wilkinson [50] developed a resistance-based system for lathe turning operations. The system is accurate; however fails when there is no continuous contact between the tool and the workpiece, which is typically seen in machine shops (example interrupted cuts, milling operations). Considering the limitations of radiation-based system and resistance based systems mentioned above; optical-based systems are the most popular direct TCM systems [51].

2.3.1 Optical-based system

Optical-based systems are the most popular direct measurement systems. Optical systems rely on the detection of the change in geometrical features of the tool for TCM [5]. Optical systems also replicate human decision making when it comes to TCM, which relies on understanding the wear morphology of the inserts [52]. Using the visual evidence of the cutting tool allows the system to be impervious to any type of noise generally present in machine shops. The direct systems, however, are affected by the cutting oil and chips surrounding the tools; therefore, the tools need to be cleaned before TCM. Even though the vision systems are considered more accurate and less affected by different noises, indirect systems have prevailed as the optical-based systems are considered invasive systems that interrupt the process flow.

Optical systems have moved from invasive systems (Where the tool is disassembled from machine tool for TCM) to non-invasive systems (Where the tool does not have to be disassembled from the machine tool for TCM). Often literature states the invasive nature of the old optical-based system as one of the disadvantages and reason for not using optical-based systems, and this has changed with the development of modern image sensing sensors as illustrated by Wu et al. and Sun et al. [16, 19].

Optical-based systems are also making a transition from systems where human intervention is needed for feature extraction to image processing and artificially-intelligent (AI) systems where the features are extracted either by image processing algorithms or autonomously by the AI algorithms. Lanzetta [52] developed a wear morphology classification system that uses threshold and recognition criteria defined by human intervention using quantitative parameters like flank wear. Image processing systems also need human intervention, but they do not rely on quantitative parameters; instead, they rely on image transformation techniques. For example, Sun and Yeh [16] used a straight line Hough transform and grayscale threshold to determine the wear morphology. Both the quantitative methods and image processing methods need human intervention to wear morphology classification. With the advancement in AI, this feature extraction step has become more autonomous and less reliant on human intervention. Wu [19] used convolution layers which help in automatic detection of the region of interest and develop useful descriptions that can be used to define the wear morphology this eliminates the need for the definition of quantitative parameters or the need to determine the image transformation as the convolution layers do them automatically.

2.3.2 Direct systems summary

The following are the takeaways from the direct systems literature:

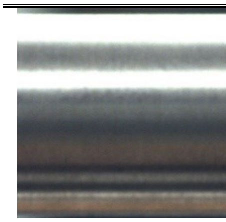
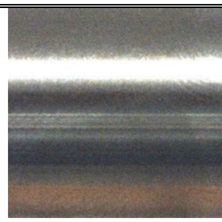
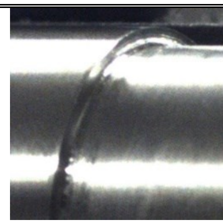
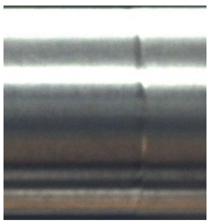
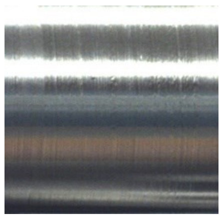
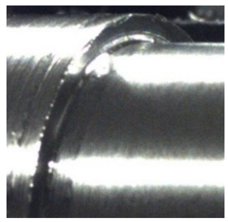
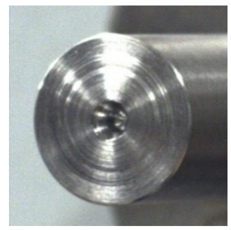
- Direct systems are more accurate because they rely on evidence that is physical changes on the cutting tools.
- Direct systems are classified as offline systems, as data acquisition can't happen during the cutting process.
- The offline nature of the direct system is not a crippling disadvantage as the systems can be designed to work in between machining cycles.
- Optical based systems are the most popular type of direct systems considering they cost less, do not pose a health risk, and can accommodate different machining operations.
- Optical based systems also the closest to the human decision-making process for tool condition monitoring.
- Optical systems are making a transition from invasive (tool needs to be disassembled form the machine for condition monitoring) to non-invasive systems (no need for a tool to be disassembled for condition monitoring).
- Optical systems are making a transition from systems that need human intervention for feature extraction (quantitative threshold and image processing techniques) to systems that do not need human intervention for feature extraction (convolution neural network-based AI algorithms).

2.4 A new definition of tool condition monitoring

TCM has seen a slow evolution of technology over the past three decades, and the evolution has made the TCM more autonomous in the last decade with the advancement in machine learning algorithms. The machine learning algorithms help in automation of the feature extraction and decision making steps, which mostly relied on expert human interventions. But the evolution is yet to yield a TCM technology that can be adopted in every machine shop in the world. The variety of ideas for TCM has further hindered the development of a deployable TCM system; various concepts of TCM as perceived by the existing literature is discussed in Section 1.2. In this section, the barriers for the current systems for their deployment in machine shops are discussed, and a new definition of TCM is also proposed. The proposed definition addresses the barriers to the deployment of TCM in machine shops.

In TCM, the existing studies are developing technologies to estimate and quantify wear on the cutting edge [15, 16, 18, 19]. But the quantification of wear on the cutting tool provides very little information about the useability of the tool. The useability of the tool is determined by the quality requirements prescribed by the engineering drawing. These quality requirements are captured in tool change policies (TCP) some of the examples for TCP are given in Table 2.1. The machine operators are looking for the reject quality indicators like poor surface finish, the occurrence of chatter marks, burr on edges, feed marks, among others. When these indicators are evident, the operator understands that the tool life is completed, and it must be changed. The quantification of wear on the tool has no direct way to describe the TCP, and this is one of the barriers for current systems for their deployment in machine shops. Therefore the primary objective of the TCM must be to carry out TCP [34].

Table 2.1 Examples of different quality indicators used by machine shops for TCP.

Surface finish	Chatter marks	Burr on edge	Feed marks	Quality
				Accepted quality
				Reject quality

Another barrier for current TCM systems is their inability to translate from a laboratory setting to the industrial setting of machine shops. There is more than one reason for the inability to translate. The inflexibility of the system to accommodate different TCP being one of them, depending on the complexity of the component being machined, a Computerized Numerical Control (CNC) machine uses more than three tools for machining the part. For example, there is a different tool for turning, facing, and finishing each tool has its TCP. The systems are not designed to accommodate the different TCP effortlessly.

On the other hand, the material of the workpiece, type of tool, and the coating grades can also vary; when one of the parameters changes, the findings from the optimized prediction systems can not be used. For example, the model trained for roughing geometry can not be used to predict the life of a finishing tool as the signals (force, vibration, and acoustic signals) generated during cutting are different. This is the inability of the systems to generalize across different applications. The specific dynamics and capabilities of the CNC can also influence the TCP. The variety of machining environment presents a mammoth challenge for generalization of TCM systems, but yet only five research papers [40, 45, 48, 53, 54] out of forty-two research papers reviewed in Annexure a for generating literature review mention generalization.

The industrial environment provides a different set of challenges, especially for indirect systems that rely on signals generated during cutting. The noise of the industrial setup, like from other machines, machine shop operations can influence the signal acquisition, which can translate to errors in predictions of tool condition.

Considering the limitations of current TCM systems and the different constraints that limit the translation of systems from the laboratory to the industrial set up; the study has developed the following definition for TCM. The following definition needs to be achieved to bridge the gap between the current TCM system and a TCM system that can be deployed in machine shops around the world.

"The quality indicators determine the usability of a tool; these quality indicators are captured in tool change policies. Tool condition monitoring is the detection, adaptation, and implementation of different tool change policies, autonomously, and independently in different industrial environments."

Chapter 3: Teaching Machines, a lesson on quality: Using CNN and transfer learning

The previous chapter identified three barriers in the existing systems that need to be addressed for a TCM solution to be implementable to carry out the tool change decision making autonomously and independently in machine shops around the world. One, these systems are not flexible to include different quality requirements of the machine shops. The existing studies only consider one quality aspect, for example, surface finish for their study, which is difficult to generalize across different quality requirements like concentricity or burr on edges commonly seen in machine shops. Second, the studies try to quantify the tool condition, while the answer that matters is if the tool produces a conforming part or a non-conforming part. Third, the qualitative answer of if the tool produces a conforming part or a non-conforming part requires a large amount of data to train the predictive models. Finally a new definition for TCM that addressed these barriers was developed.The system proposed in this chapter is the implementation methodology for the proposed new definition. The system is using the concepts of computer vision, Convolution Neural Network (CNN), and Transfer Learning (TL), to teach the machines how a conforming component producing tool looks and how a non-conforming component producing tool looks.

3.1 Introduction

The last decade has been the decade of the fourth revolution in the industry (Industry 4.0) for manufacturing around the world using smart systems and technology. Industry 4.0, uses concepts of machine learning and big data to reduce waste of time and resources and makes the production process more efficient [55]. The concepts of Industry 4.0 require machines that are smart and autonomous [56], and this presents an excellent opportunity for the development of machine learning algorithms that improve the operations and help in the reduction of wastes.

Smart systems are essential for the implementation of Industry 4.0 in machine shops, but what is the definition of a smart machine in the context of machining quality control. There is no clear definition proposed in past studies. A smarter machine in the context of machining quality control can be understood as a machine with the intelligence to understands and implement the quality requirements. This machine only produces the parts that meet the design requirements or conforming parts and detect the changes in machining parameters or environmental factors. These changes in environmental factors might result in the manufacturing of parts that don't meet the design requirements or non-conforming parts. In other words, the machine has the intelligence to predict if the machine produces a conforming part or non-conforming part based on the environmental inputs.

In a mass manufacturing facility, the environmental factors like machine used, jigs, and fixtures in which the machining is taking place are reasonably stable, and there are changed only when the production lines are repurposed to produce different components. Given the stable environmental factors, the quality of the machining largely depends on the consumables like cutting tools, coolant oils, among others used by these machines processes [43, 57]. If the consumables are used for too long, they contribute to the production of non-conforming parts, and if the consumables are underutilized, they add to the overheads and wastage [58]. The process of defining the limits for an overused and underused tool can be termed as a Tool Change Policy (TCP) illustrated later in Section 3.4. In an intelligent TCM system, the definition and implementation of TCP should be carried out autonomously and independently.

TCM is one of the classical problems of manufacturing, and it is extensively studied in the last four decades [5]. However, three barriers have been identified by the presented study that challenged the deployment of existing studies in machine shops around the world. One, the inflexibility of the systems to accommodate different TCP, tool condition affects different aspects of machining like surface finish, dimensional accuracy [35, 59]. For example, TCP for one tool is when the chatter marks start to appear, while another tool TCP is related to a burr on edge. The existing studies fail to provide flexibility to accommodate different TCP.

Quantification of tool wear ignores the concept of TCP and diverts the attention to the quantification of wear on inserts, and this is the second identified challenge for deployment of current TCM systems. The studies try to quantify the wear on inserts in terms of millimeters of flank wear [15, 16, 18, 19]. This quantification provides no information about the usability of the tool. In machine-shops around the world, quality management is not seen as a process that directly adds value to the component, and from an economic point this process must be limited to absolute necessary [60]; that is why the manufacturers are interested to know if components meet the design requirements (a conforming part) or they do not meet design requirements (a non-conforming part). One of the examples for this qualitative approach is GO (conforming part) / NO GO (non-conforming part) gauges [17] discussed later in Section 3.3. Therefore, the central objective of TCM must also be qualitative that recognizes the GO (tool that produces conforming part) quality tool and NO GO (tool that produces non-conforming part) quality tool.

The final barrier identified is the large amount of data and time required to collect and train these systems, which is the most significant barrier in the accommodation of different TCP. The models have to be retrained for different quality requirements that require changing the parameters learned by the predictive systems. For example, Wu et al. [61] used 5880 images to train the model for the detection of different wear patterns. Considering four cutting edges per insert, the model has used 1470 inserts to train the model. Collecting these extensive data for every machine and TCP is infeasible considering hundreds of different quality requirements in machine shops around the world.

The proposed system is an integrated solution to the three barriers mentioned above. The system relies on monitoring the wear of cutting tools and classifies the tools as GO / NO GO tools that help the machine operator take the decision of whether the tool can be used for the next machining cycle. The system uses state of the art tool wear classification CNN and principles of TL. These concepts are discussed in Section 3.3. The novelty of the system is its ability to correlate the tool condition with machining quality and the accommodation of different quality requirements using TCP with the requirement of fewer data to achieve the accommodation.

The rest of the chapter is structured as follows; in Section 3.2, the relevant studies are discussed. Section 3.3 explains the methodology used in the system, which can be divided into offline state and online state. In Section 3.4, the case study and the implementation of the proposed system are discussed. The methodology is evaluated in Section 3.5, followed by the suggested future direction in the tool condition monitoring. In the last section, the conclusions drawn from the study are discussed.

3.2 Qualitative TCM literature review

The TCM methods are classified into direct and indirect methods [62]; direct methods mostly involves the use of computer vision [16, 19], radiation [49], electrical resistance [50], whereas indirect methods use online monitoring methods that use vibration [8–10], force [8], temperature and sound [7] signals. Indirect methods are less complicated and can be implemented straightforwardly and monitored in real-time [59] but, they are prone to noise and are less accurate than the direct methods [63]. Real-time monitoring is also not a crippling disadvantage for direct systems as there is enough time in between machining operation and cycles [13] to get the required data without disturbing the sequence of operations of a machine shop. Also, the unidirectional execution of existing G-code based systems doesn't allow for real-time changes in the machining parameters [64–66] therefore, there is no way to integrate the response generated by indirect systems in real-time. Considering direct methods are more accurate systems, the study adopts the direct monitoring methodology.

Vision-based systems are the most popular systems when it comes to direct TCM systems. Vision systems have also improved in recent years and are being used in different facets of machining like collision avoidance [67, 68] which also demonstrate the ability of vision systems to detect changes while maintaining distance from cutting process. The computer vision systems are used to monitor the changes in wear morphologies of an insert. Wear morphology classification has attracted many studies in the past years; Lanzetta [52] used vision systems for wear morphology classification using quantitative definitions of different wear patterns. The conventional TCM used in machine shops use the quantitative approach. For autonomous systems, the quantitative approach proves difficult for implementation considering the variety of qualitative parameters that need to be hardcoded into the system to identify a variety of wear morphologies. The hard coding of parameters is also computationally expensive; thus, there is a need for a system that identifies the features of different types of wear. The need for identification of different morphologies is satisfied to an extent using CNN by Wu et al. [61]; this study has inspired the base wear classification model discussed later in Section 3.3.1.

Autonomously detecting the damages to the inserts before they are used in machining is one of the essential solutions in making the tool monitoring autonomous. Fernandez-Robles et al. [69] developed a vision-based system to detect the broken inserts in the milling cutters automatically. Sun et al. [16] used image processing and image segmentation techniques to develop a system that could identify built-up edge, fracture, and other insert deformations. These studies used image processing techniques, which require human intervention to develop features descriptions; this limits the independent implementation of these systems for a variety of wear morphologies. As opposed to image processing techniques, the CNN approach learns to identify the Region Of Interest (ROI) and features description to identify different wear morphology, and this eliminates the need for human feature descriptions step needed in other techniques [70]. Considering the utility of autonomous feature extraction, the proposed study uses CNN approach for tool condition monitoring.

Even though TCM is one of the classical problems, there are fewer publications in the context of correlation of tool condition with the quality of the component. Jain and Lad [71] developed a system that correlates tool condition and production quality. The study also developed a multi-level categorization of the wear using support vector machine methodology. Jain and Lad [72] study explored the relationship between the surface finish and tool wear and found the Pearson correlation coefficient between surface finish and tool condition to be significant to establish a strong correlation. The study used a random forest-based fault estimation model to get the relation between surface finish and tool condition. Grzenda and Bustillo [73], developed a semi-supervised model to predict the surface finish using the vibration signals, Fourier transformation was used to transform signals to frequency space, and further only the relevant frequency ranges wear considered for the study. Wu et al. [61] developed a two-stage system that aimed at determining the type of wear in the first stage and tried to quantify the wear of the insert in a milling cutter. The system uses CNN to determine the type of wear, and the wear value is obtained using the relation between image pixel value and actual value and width of the minimum circumscribed rectangle. Dutta et al. [74] used surface texture descriptions to determine the tool life using the grey level co-occurrence matrix, the images of the resulting surface finish were captured, and the tool wear was measured using a microscope. García-Ordás et al. [63] used a computer vision system to determine the usefulness of the milling cutters. The system used a support vector machine methodology to classify the wear patterns. The system identified the state of the tool with about 90 percent accuracy.

The studies mentioned above correlate the tool condition with the specific quality and design requirements like surface finish. As discussed in Section 3.1, there are a variety of quality and design requirements that are defined by TCP. These different TCPs form the ultimate definition of TCM; considering this, a TCM that is flexible to accommodate different TCP is the need of the hour. Most of the studies are also limited by the materials and tool geometries they have used, changing any one of the factors means the findings of the studies can not be used. For the TCM to be autonomous and independent, it must be capable of working with different materials and tool geometries and tool coating grades. The requirement of flexibility to work with different TCP and the ability to generalize the system for different working materials, tool geometries and tool coating grades form the basis for the development of the proposed system.

3.3 Qualitative TCM system

The system is developed to operate in three stages, as shown in Fig. 3.1. The training of the base model is where the architecture of the base model and the central intelligence of the system is developed; this training is done remotely. The architecture and training parameters of the base model are discussed in Section 3.3.1. The offline state of the system is operational in the machine shops when the production lines are set up. In this state, the system is receiving training to identify the TCP. The knowledge from the base wear classification model is used to expedite this training process using the TL technique discussed later in Section 3.3.2. The output of the system is inspired by the GO / NO GO gauges. The goal of GO gauge is to accept as many good parts as possible that satisfy the material condition specification, and NO GO gauges are designed to reject all the parts that violate the material condition specification [17]. The GO / NO GO gauge in this system

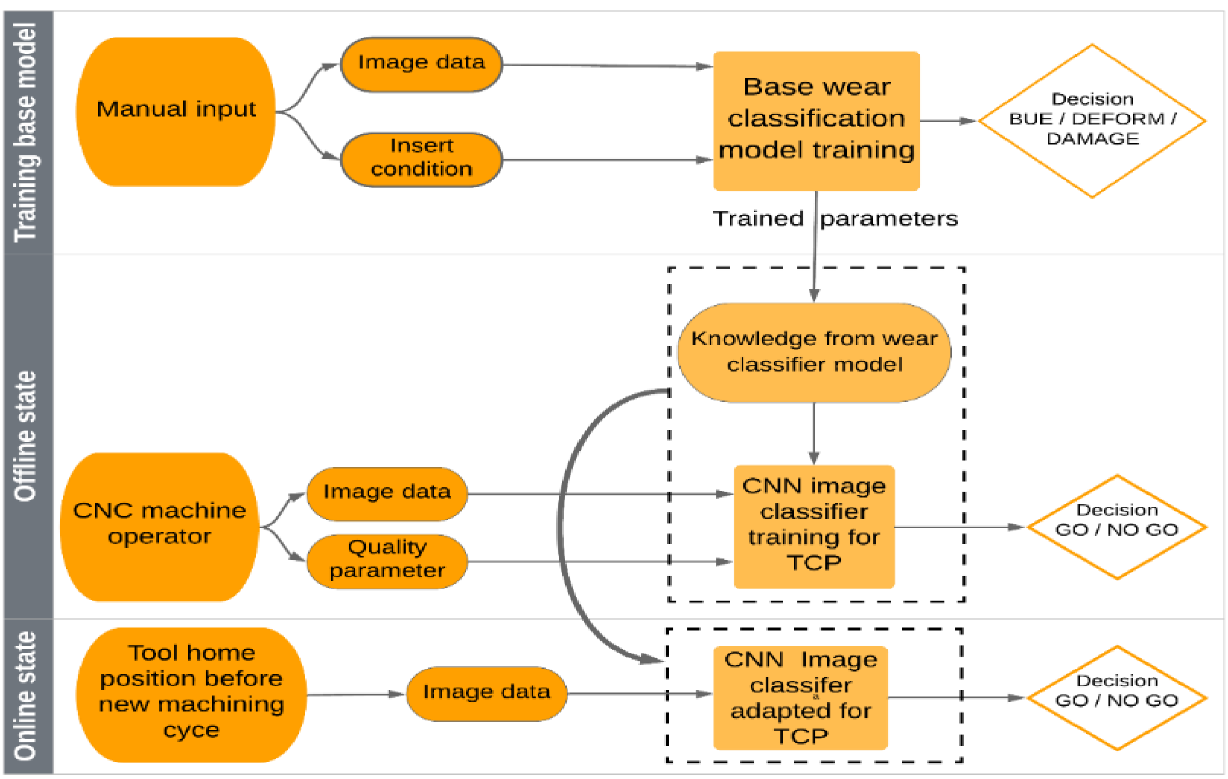


Fig. 3.1 Overview of the system architecture

is envisioned as an implementation of TCP. When a tool of GO quality is detected, the tool is accepted and used for production. Similarly, when a NO GO quality tool is detected, the operator is asked to change the tool before resuming the production. The GO / NO GO arrangement allows for the flexibility to adapt the system for different TCP. In the online state of the system is discussed in Section 3.3.3, the system is executing the TCP autonomously after every machining cycle, making sure the tools are in GO condition before they are used, and in this way, prove a proactive approach to TCM.

3.3.1 The base wear classification model

CNN is one of the most promising approaches to image processing and pattern recognition [70]. CNN layers are part of the architecture; it is standard practice to use convolution layers at the starting of the model to develop feature descriptions of the images. These layers are good at narrowing down the ROI and require less computational memory when compared to conventional models. These are the reasons they have seen a wide range of applications in a variety of areas, from hand gesture recognition [75] to disease recognition in plants [76]. One of the other advantages of the convolution layers is its ability to extract features autonomously. Some of these transformations are shown in Fig. 3.2. In Fig. 3.2 b, each row is the output of convolution or max-pooling layers. It can be seen in the successive layers. The layer transformation and filtering further define the description of the wear features. This step in image processing techniques is done manually, which is the disadvantage of image processing techniques.

The base model architecture used by the system is shown in Fig. 3.3The input to this architecture is a 200*200*3 Red Green Blue image (RGB). The convolution layers have sparse interaction with the input of the previous layer [77]. For the convolution layer, 3*3 kernel is used

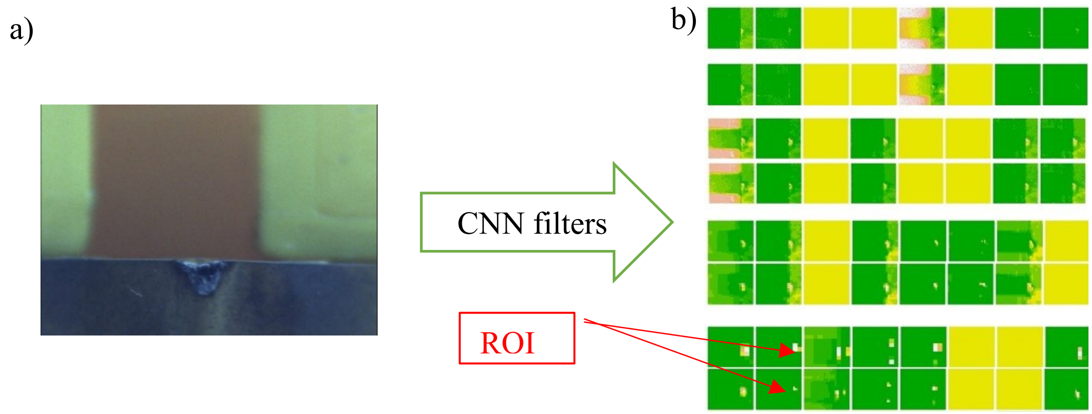


Fig. 3.2 Image transformation and filtering by convolution and max pooling layers

with 32 filters in the first and second convolution layers. For the last two convolution layers, 64 filters are used with 3*3 kernel. A kernel can be imagined as a 3*3 window sliding over 200*200 in the step of a one-pixel slide. This concept helps in the detection of small meaningful features and also reduces the parameters to be stored and computed [77]. The output of the convolution layer is then fed to the pooling layer, in the case of the developed model, it is max pooling layer, where kernel reports the maximum value of the kernel size input. This layer helps in making the model more robust in response to small translations to the inputs [77]. This is summarized in equation 1, where A is the crrosponding pixel value in row i and column j, and this equation is valid for the 2*2 kernel used for max pooling layers.

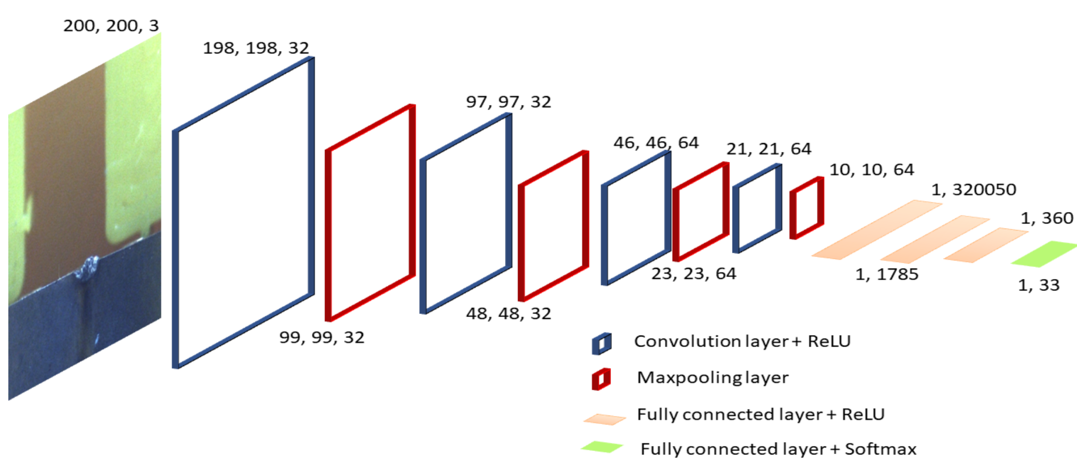


Fig. 3.3 Base CNN architecture with respective size of the layers for insert wear classification

Max pooling layer

$$O_{i,j} = \max \{ A_{i,j}, A_{i+1,j}, A_{i,j+1}, A_{i+1,j+1} \} \quad (1)$$

The output of the last max-pooling layer is then flattened to $1*n$ vector, which forms the input to the Fully Connected Layers (FCL) for further processing, where n is the number of inputs to the neural network. The number of inputs n also determines the width of FCL of the network.

FCLs are the basic type of neural network where each input interacts with each output of the previous layer [77], the different layers in the network are modeled as different functions, which are the function of the previous layer. In the proposed model shown in Fig. 3.3 base model, we have four FCL layers which can be written as $f^{(1)}$, $f^{(2)}$, $f^{(3)}$ and $f^{(4)}$ respectively therefore using the chain concept we can rewrite these function as $f(x_i) = f^{(4)}(f^{(3)} (f^{(2)} (f^{(1)}(x_n))))$ [77], where x_n is the data from the convolution layers. The objective of the neural network is to best estimate $f(x_n; \theta)$ to function $f^*(x_n)$, where $f^*(x_n)$ is the ideal (real-world relation) function that maps the inputs from the convolution layer to their classes of wear and θ is free parameter adjusted to optimize the best estimation of ideal function [77].

The architecture in Fig. 3.3 uses a rectified linear unit (ReLU) activation function in the intermediate layers, which is a common practice for CNNs to improve the training speed [76]. ReLU returns zero for half of its domain and input for the other half of the domain that is zero for inactive nodes and node output for active nodes, which helps make the gradients of the loss function large and constant [77]. ReLU is used in all the layers except the output layer in the proposed model shown in Fig. 3.3. ReLU is summarized in equation 2, where z is the output of the node.

$$\mathrm{ReLU}(z) = \max\{0, z\} \tag{2}$$

The softmax activation function was used in the last layer of the base model architecture, which is also common in multiclass classification CNNs [76]. Softmax activation usually used in the output layers of the neural networks gives the probability distribution over n possible values. It ensures the prediction of z belonging to a class for n different classes is between 0 and 1, and the sum of probabilities is equal to 1 [77]. This is summarized in equation 3, where z_p is the output of the node for p class.

$$\mathrm{softmax}(z_p) = \frac{e^{z_p}}{\sum_{c=1}^{3} e^{z_c}} \tag{3}$$

The loss of a model can be defined as a function that quantifies the performance of the system [70]; the study uses categorical cross-entropy as the loss function. ADAM, which is a stochastic optimizer that is computationally efficient and combines the advantages of RMSProp and AdaGrad [78], was used to optimize the weights of the base model. This facilitates faster convergence to an optimal solution[78]. The parameters used in ADAM are learning rate = 0.001, $beta^1 = 0.9$, and $beta^2 = 0.999$. The algorithm for ADAM implementation can be found in [78].

3.3.2 CNN image classifier trained for TCP

The base model developed and discussed in Section 3.3.1 forms the central intelligence for the TCM. The base model helps narrow down the ROI and extract useful features and descriptions of the tool, as shown in Fig. 3.2. This intelligence is developed in the base model is rolled out as a trained network. The offline stage of the system is in the machine shops, where the model has to be repurposed to identify and implement different TCP. Considering that there are thousands of different TCP unique to each machine shop, retraining a complete network presents a significant data and training time challenge. TL is one of the lifelines to overcome this data and training time challenge.

Given the importance of TL, we now adapt the definitions of TL in [79] for our application. In the proposed system, the knowledge developed during the training of wear classification model that is trained to identify what type of wear pattern or damage the cutting tool has is optimized using TL to differentiate between a good tool that produces conforming parts and a bad tool that produces non-conforming parts. Every classification model has a domain D, which forms the pool for data extraction and a task which, in the case of the study, is classification. Pan and Yang [79] define domain D consisting of two components a feature space X and marginal probability P(X). Task T also consists of two-component Y labels and a predictive function f(.), since neural networks have a large number of trainable parameters they can choose from different functions that best predict the tasks which in the case of study is image classification. Therefore $\mathrm{D} = \{\mathrm{X}, \mathrm{P(X)}\}$ and $\mathrm{T} = \{\mathrm{Y}, \mathrm{f(.)}\}$, considering these definitions, we can define source domain and target domain. The source domain is images captured form cutting inserts used in machining (D_S), and the task is to identify wear type classification (T_S). Similarly, the target domain is images of inserts used in production (D_T), and the task is the quality classification (T_T).

The images for the base model are drawn for the inserts used in production. Similarly, images used for the target model are also drawn from inserts used in production. Therefore, the methodology is built around the assumption that the images for the source and target model have a similar domain, which is reasonable considering that the images used to train base model wear morphology classification are also used in production in a machine shop. Given the similarity of domains, $X_S = X_S$, $P_S(X) = P_T(X)$, and $D_S = D_T$, that is, the feature space, and the marginal probability of data distribution for both models, are the same.

The tasks of source and the target models are different as the labels are different, therefore $T_S \neq T_T$ as the $Y_S \neq Y_T$, as given by equations 4 and 5. But the predictive function could be similar or different since the neural networks are black-box models. There is no way to know if the same or different function was used for source and target tasks.

$$Y_S = \begin{cases} 0 & \text{if the insert is damaged} \\ 1 & \text{if the insert has deformation} \\ 2 & \text{if the insert has normal wear} \end{cases} \quad (4)$$

$$Y_T = \begin{cases} 0 & \text{if the component is Conforming (GO)} \\ 1 & \text{if the component is Non} - \text{conforming (NO GO)} \end{cases} \quad (5)$$

The target task is tied up to the traditional concepts of GO/NO GO gauges discussed at the start of Section 3.3. GO / NO GO gauges are one of the most popular gauges to evaluate the material conditions in holes and shafts. The TCM system developed extends and generalizes this definition of GO/ NO GO gauges to other quality requirements. In the target task, the model is retrained to identify a GO part producing tool and NO GO part producing tool. This concept makes the proposed methodology qualitative and gives the model the flexibility to adapt its knowledge across different TCP. The offline state requires an expert to generate the GO / NO GO labels for the training and adaptation of the task to TCP.

3.3.3 CNN image classifier adapted for TCP

The online state of the system is working seamlessly without the need for human intervention to identify the tools that produce a NO GO part. The system takes a picture before the machining starts and, based on the training during the offline state, classifies the tool as a useable or unusable tool. There are many tools on the machine, and the quality demand from each tool is different. Therefore, the offline part of the system where the tool condition is associated with GO / NO GO quality of operation has to be done to each tool during the production setup. This allows the system to run without quality inspection in the online state.

3.4 Qualitative TCM system experimental setup

The images of the CNMG 120408/12, TNMG 160408/12, and VNMG 160408 turning inserts used in the turning application are captured using the DFK 33GP006 GigE color camera with TCL 3520 5MP lens. Initially, the top, side, and front views are considered for the classification. A processor with Intel i7 and 16 GB RAM was used to develop the classification model, and the models were implemented using R computer language with kears package using TensorFlow backend. The examples of these pictures can be seen in Table 3.1. Table 3.1 shows that the top and side view provides very less description of the type of wear, and the wear is easily distinguishable in fount view images; therefore, only fount view images were considered for the classification model. The setup for capturing the images of different views can be seen in Fig. 3.4. The images are captured in standard room lighting without any dedicated light source. As we can see from Fig. 3.2, the background of the insert has no impact on the feature extraction process.

Table 3.1 Wear patterns and different views

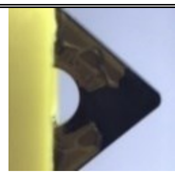
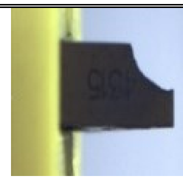
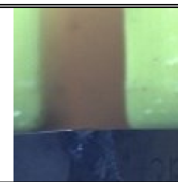
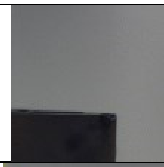
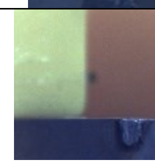
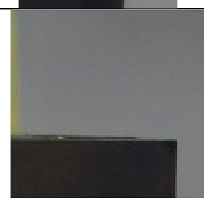
Wear pattern	Top view	Side view	Front view
Damaged			
Deformation			
Abrasive			

Fig. 3.4 Image capturing station

The process starts with collecting the front-view images of the inserts for three different categories, 79 images were captured of damaged inserts, 121 images of deformed inserts, and 128 images of abrasive wear inserts were captured. All the pictures were then resized to 200 pixels (width) x 200 pixels (height).

The model must be made robust against variation and transformation one of the ways to do this is to use data augmentation where the data is subjected to various transformation like rotation, flipping, shearing the images this helps in improving the generalization error as the model is trained to be invariant to these transformations [77]. The training dataset was then subjected to data augmentation, with an allowed rotation range of 10 degrees, width shift range of 20 percent, height shift range of 10 percent, zooming range of 20 percent. The parameters for augmentation were chosen carefully not to alter the wear description of the images but to accommodate for poor quality images that can be seen when the system is deployed in machine shops. An example of this data augmentation can be seen in Fig. 3.5. It must be noted that the validation images wear not subjected to data augmentation.

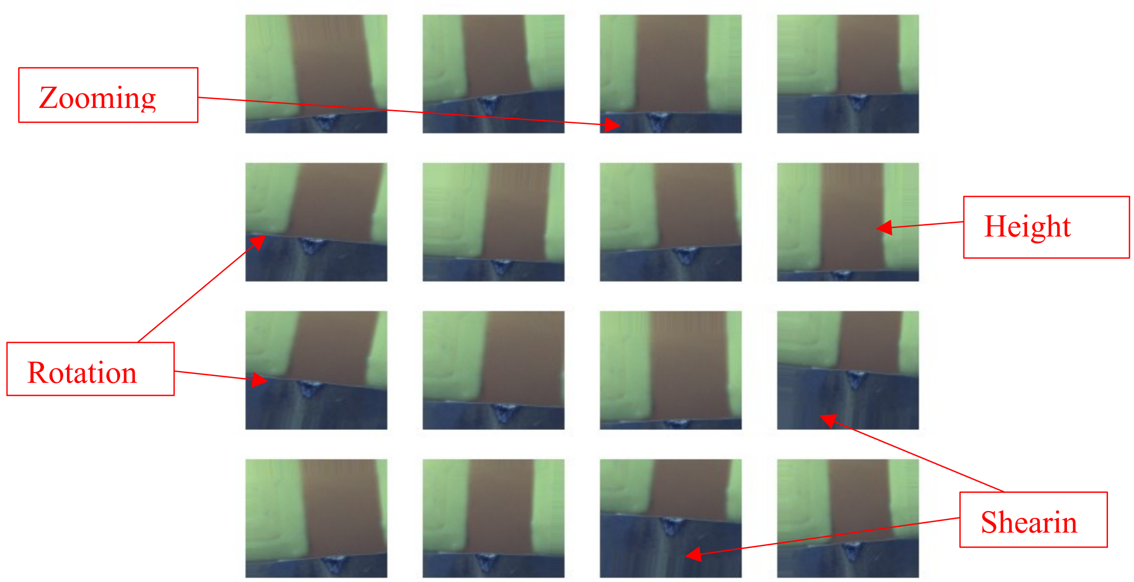
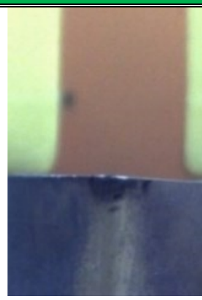
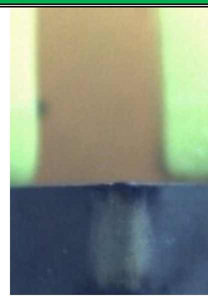
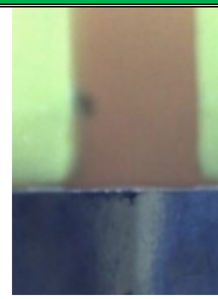
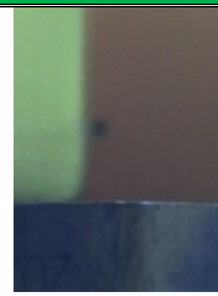
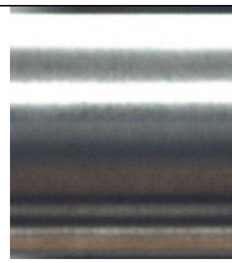
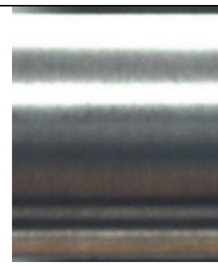
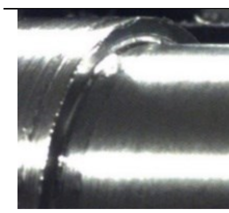
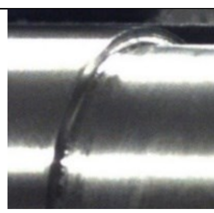
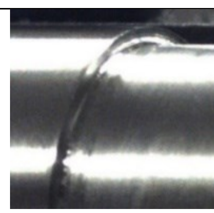
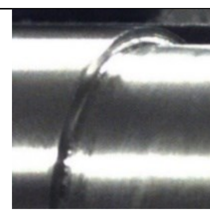
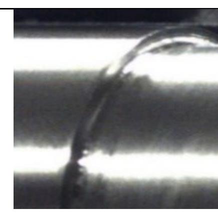
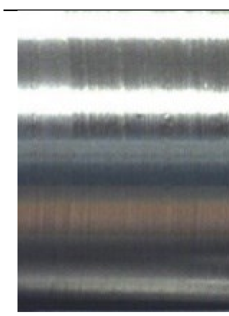
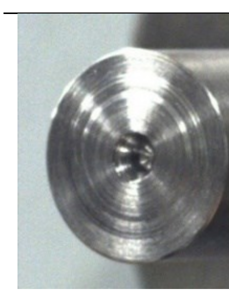


Fig. 3.5 Examples of rotation, shearing, height shift and zooming data augmentation applied to training images

The augmented data is then fed to the neural networks. The images were first subjected to the image transformations of the convolution and max-pooling layers, where the ROI is identified, useful features are extracted from the images autonomously. The data in the final layers form the last max-pooling layer forms the input to the densely connected layers. The images are converted to pixel data, and each pixel forms the input to the first FCL the data is mapped to the labels of the pictures, the output of the FCL is the prediction of wear type. The base model can now identify the nuanced differences in the cutting insert by identifying if the insert has deformation, normal wear, or damage. The knowledge developed in the base model can now be used to identify the change in quality by retaining the model.

For the target model, the images of inserts are classified into GO / NO GO categories ; for this part of the study, only CNMG 120408 turning inserts are used; one of the examples for GO / NO GO can be seen in Table 3.2. Table 3.2 also gives an example for different TCP accessible in machine shops. The objective of the case study with respect to the target model is to prove that the model identifies the nuance differences in change in wear morphology and predicts the consequence of using a tool that is if the tool produces a GO quality part or NO GO quality part while using lesser images and training time and iterations so that the TCP deployment is fast-tracked.

Table 3.2 GO, NO GO, and examples of different tool change policies used in machine shops around the world

NO GO	GO	GO	GO	GO	Quality
					Insert wear image
					Surface finish
					Burr on edge
					Chatter marks
					Feed marks

For this part of the study, the inserts that are relatively new and have typical wear patterns are manually classified as GO category inserts, and the inserts that have higher wear levels, as shown in NO GO part of Table 3.2, are classified as NO GO category inserts. These images are used to train the target model, and the training images are subjected to similar data augmentation shown in Fig. 3.5. The architecture of the target model is shown in Table 3.3. The parameters learned by the base model are frozen, and only 382 parameters of layers 12 and 13 are optimized for the target model.

Table 3.3 Target model architecture

	Layer type	Input Shape	Output Shape	Filter Size	Trainable Parameters
	Input layer	200,200,3	200,200,3	0	
1	Convolution layer	200,200,3	198,198,32	3,3,32	0
2	Max pooling layer	198,198,32	99,99,32	2,2,32	0
3	Convolution layer	99,99,32	97,97,32	3,3,32	0
4	Max pooling layer	97,97,32	48,48,32	2,2,32	0
5	Convolution layer	48,48,32	46,46,64	3,3,64	0
6	Max pooling layer	46,46,64	23,23,64	2,2,64	0
7	Convolution layer	23,23,64	21,21,64	3,3,64	0
8	Max pooling layer	21,21,64	10,10,64	2,2,64	0
9	flatten (Flatten)	10,10,64	6400,1	0	0
10	Dense layer	6400,1	50,1	0	0
11	Dense layer	50,1	35,1	0	0
12	Dense layer	35,1	10,1	0	360
13	Dense layer	10,1	2,1	0	22

3.5 Qualitative TCM system results and discussions

The training of the base model was carried out using 223 images, and 105 images were split from original dataset for validation; the validation data set consists of approximately 33 percent of each damaged, deformation, and abrasive wear categories. Fig. 3.6 (a) gives accuracy for base model training runs. The validation accuracy stabilized around the 200th epoch, and the validation accuracy is 83.75 percent. Fig. 3.6 (b) presents the loss of over 250 epochs, and the loss is the indication of the magnitude of deviation between prediction and the actual value.

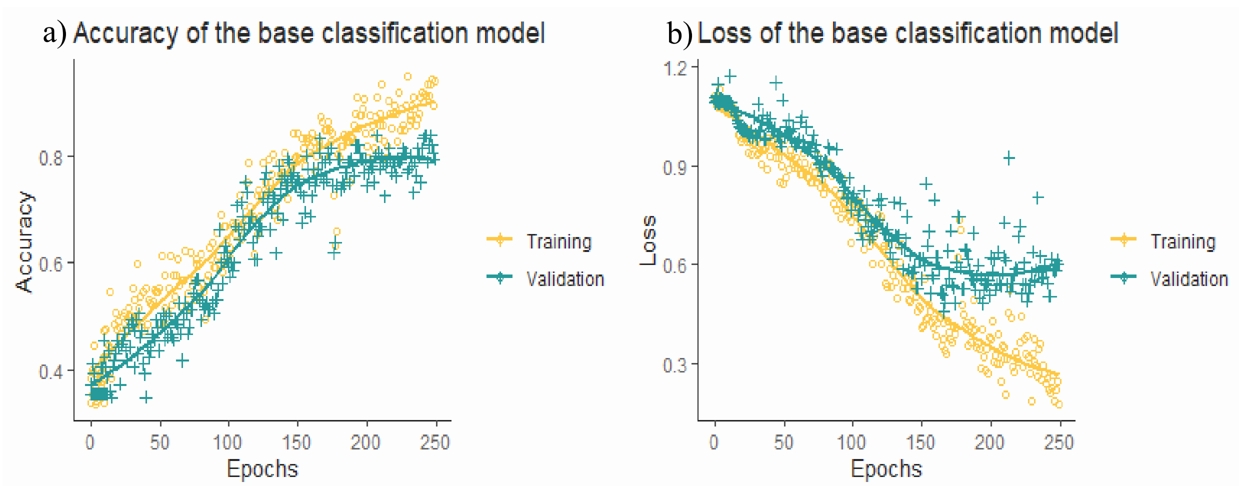


Fig. 3.6 (a) Accuracy of the base model. (b) Loss convergence graph of the base model

For the second part, the objective is to demonstrate the capability of the system to adapt to the new task of TCP deployment using fewer images and less training time. For this, the data is partitioned into three sections, training, validation, and test dataset; various training runs are carried out using a different number of images. The summary of the number of images used for each run is shown in Table 3.4. All the images in the three sections are different and were not repeated. The images in the test data set can be seen in Fig. 3.7; the GO category images have no wear or have typical wear pattern; these tools produce conforming parts, and the NO GO category have visible wear on the edges; these tools produce non-conforming parts.

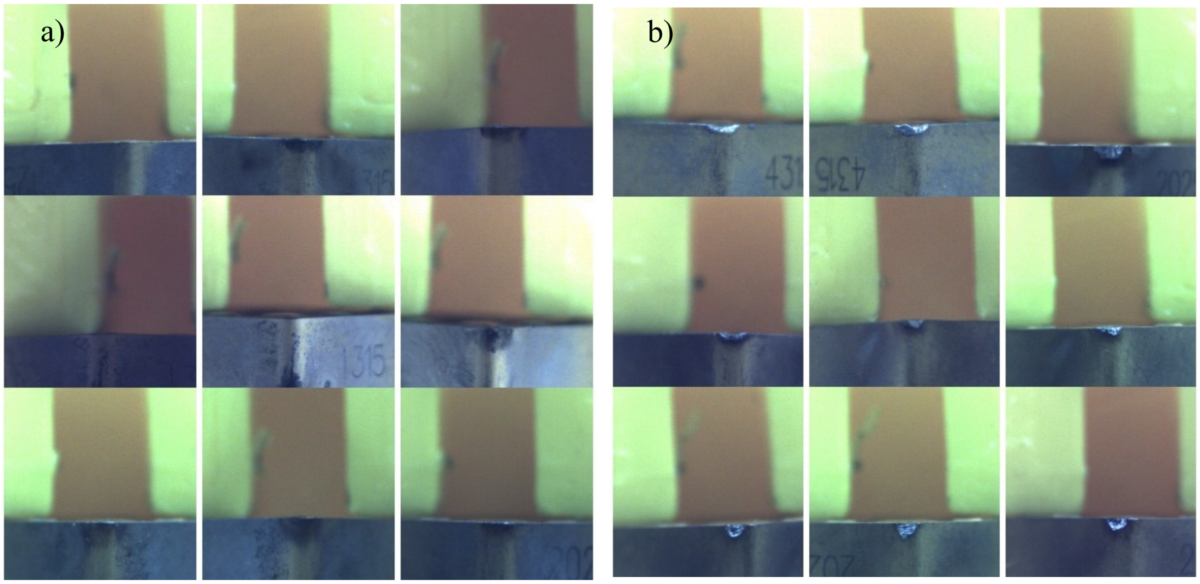


Fig. 3.7 Test image data a) GO images b) NO GO images.

Table 3.4 Training, validation, and test data split for different runs

RUN	Training pictures	Validation pictures	Test pictures
1	13	10	20
2	18	12	20
3	23	16	20
4	27	18	20
5	37	26	20

Table 3.5 Confusion matrix for run 5

Actual \ Prediction	GO	NO GO
GO	7	0
NO GO	3	10

Fig. 3.8 shows the accuracy and loss values for different runs. It can be seen from Fig. 3.8 b the loss value plateaued around the 5th epoch in most of the runs signifying that the optimization of the parameters requires fewer iterations, which enables the system to accommodate a variety of

TCP and with less training requirements. Fig. 3.8 c and d show the accuracy and loss of the trained models on the test dataset. It can be seen that the accuracy of the models is increasing with the number of images used in training the model. Run 4 had lesser loss value when compared to run 5 but yet had lower accuracy; this can be attributed to overfitting of data which led to miss classification of images in NO GO category test data as GO category. Run 5 had the best results in terms of accuracy on test data where 37 images are used in training the model. The accuracy on the test data for run 5 was 85 percent; the confusion matrix for run 5 can be seen in Table 3.5. The model predicted all NO GO label images correctly and predicted 3 images of GO labels incorrectly.

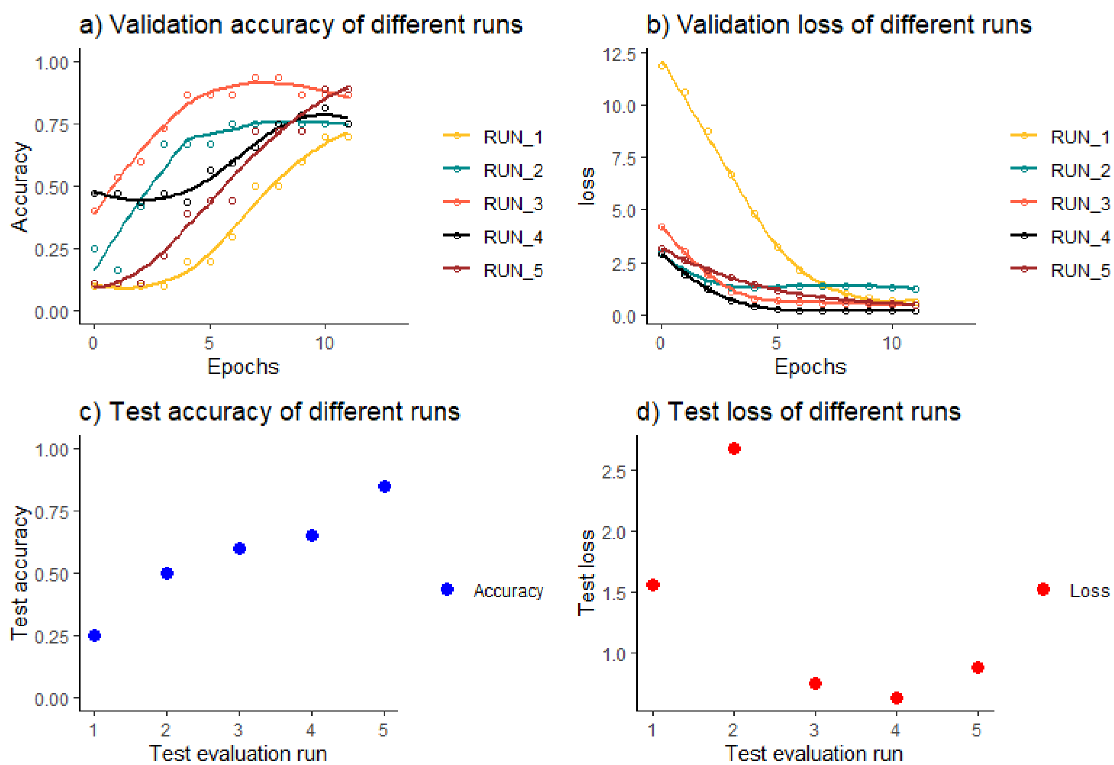


Fig. 3.8 Results for target model training run on validation and test datasets

The final part of the study is the deployment of the system using a Graphical User Interface (GUI). Fig. 3.9 gives a view of the GUI; the output of the GUI is feedback to the operator. The feedback is NO GO for tools that the target model predicts will produce a non-conforming part, and GO for tools that the model predicts will produce a conforming part. The machine operator is encouraged to replace the tool when the GUI displays NO GO. The prediction is generated within 5 seconds, facilitating the mass production without interruptions of quality inspections.

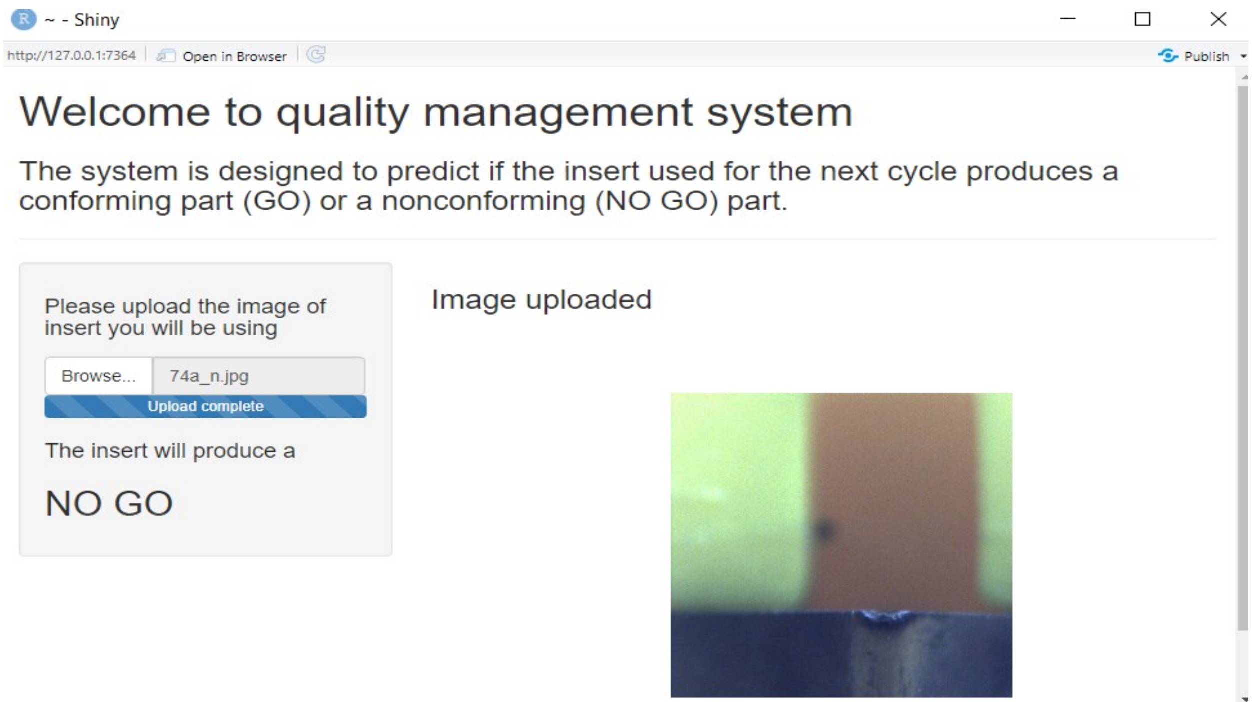


Fig. 3.9 GUI for quality management system

The proposed system directs the TCM from a quantitative to a qualitative approach using TCP, and this makes the system more flexible to accommodate different quality requirements seen in machine shops around the world. The system uses feature extraction capabilities of CNN and the ability of these models to learn new features using TL. Future development in the proposed system has three fronts; first, the development of the camera system to be integrated into the machine, the image acquisition in the study was independent of the machine, but the system has demonstrated that the images acquired from a reasonable distance away from the cutting operation can be used and classified by the system. The system used standard room lighting; There are systems discussed in studies done by Sun et al. [16], which are capable of generating the required light intensity and protecting the camera from the cutting oil. Second, the improvement of intelligence and accuracy of the system by integrating more diverse wear images into the base model, since the base model is the central nervous system and target models have similar data distribution, the accuracy of GO / NO GO model can be improved with fewer iterations requirements, with a more robust base model . Finally, the proposed system is designed for the turning process, considering that the wear mechanisms in milling are different; there is a need to develop a similar system for milling applications. A similar neural network can be trained with milling inserts data to repurpose the framework for a milling application. The CNN architecture is a standard approach when it comes to image recognition, and identification-related neural network architectures, the area of deep learning also continues to evolve; therefore, there is a need to keep an eye out for new techniques that can improve the training time and accuracy of the system.

3.6 Conclusion

The proposed study redirects the TCM from tool wear quantification to the objective of providing a more proactive qualitative approach to quality management that saves the resources used in the production of non-conforming parts. A tool change policy is employed to detect these changes in quality indicators and change the tools when they occur. Given the different quality requirements, there are a variety of tool change policies. Therefore, a TCM that is flexible to adapt to different tool change policies is developed. The developed systems can adapt to a new tool change policy requiring as few as 37 images and 12 training iterations using concepts of transfer learning and convolution neural networks. The study also developed a qualitative approach to TCM since the answer that is more important than quantifying the wear on cutting tool is the answer to if the tool produces a conforming part or a non-conforming part. This is captured in the system by extending the concept of GO / NO GO gauges to different quality requirements through tool conditions. The tools that are predicted to produce a conforming part are categorized as GO tools, while non-conforming part producing tools are classified as NO GO tools. The developed system can identify the GO / NO GO quality tool with 85 percent accuracy. Lastly, a graphical user interface is also developed to give feedback to machine operators about the usability of the tools. The system is designed to operate in between machining cycles, checking the usability of every tool before they are used. The system only takes a few seconds to determine the usability of the tools. This concept helps in making the proposed methodology an in-process TCM system.

Chapter 4: Improving tool life by optimizing machining parameters: Using autonomous fuzzy logic controller and image data

In the previous chapter, the ability of the CNN model to detect the nuanced differences in wear morphology is demonstrated. In this chapter a machining parameter optimization system is developed using the ability of CNN to detect different wear morphologies. Optimization of machining parameters like cutting speed, feed, and depth of cut is one of the extensively studied fields in the past two decades [80]. While researchers agree optimization of these parameters is essential, there is no conscience as to what the objective of the optimization should be. The studies consider production cost, production time, surface finish, among others, as the objective of parameter optimization [20–26, 81, 82], but there are very few studies that consider the manufacturer prescribed tool life as the criteria for parament optimization. It is worth noting that every tool is designed to achieve manufacturer prescribed contact time or length. When the tool is used under abrasive wear conditions which tooling engineers call normal flank wear, the prescribed tool life or full utilization of cutting edge is achieved [28]. Therefore, the objective of machining parameter optimization must be to achieve desired outcomes in the context of reasonable tool life. The methods used by studies that do consider tool life [83–85] as an optimization objective are facing challenges to generalize when the machining material changes or the tool geometry changes. Considering this, a novel image feedback using a convolution neural network-based method combined with principles of fuzzy logic is used to optimize machining parameters. Since the system is based on online feedback from the images of the inserts, it can be used for different materials, and the system is invariant to the different tool geometries, and grades as the decisions are based on the wear mechanisms detected. The hybrid system is validated through experimentation; the results of the experiment concluded that the tool life could improve by up to 100 percent with the use of system suggested machining parameters as discussed later in Section 4.4.

4.1 Introduction

In the past decades optimization of machining parameters like cutting speed, feed, and depth of cut are extensively studied. The studies are warranted as these parameters affect different facets of machining, which include but not limited to surface finish, load on the machine, power consumption, tool life [80]. Considering this, the objectives of the optimization of these parameters have also been different. Usually, these parameters are optimized at the initial stages of the production setup through trial and error and are mostly based on the expert knowledge of the machine operator and empirical rules in machine data handbooks [86]. If the tooling engineer has selected the right tools for the right material conditions, and the machine operator has selected the right machining parameters, the manufacturer prescribed tool life, as well as other desired outcomes, are achieved. The studies that consider various objectives for parameter optimization have ignored tool life as a criterion for optimization. Considering that tooling can account for up to 12 percent of the production cost [5], it is essential to optimize other outcomes like surface finish, power consumption, keeping in mind tool life.

The studies so far take an experimental approach to get the best tool life in which various machining parameters are tried, and the parameters with the best tool life are adopted. This approach presents a challenge of generalization, when the tool geometry, coating grades, or the workpiece material changes, the assumptions in the experimentation of the studies render the optimized parameter unusable. Tool manufacturers prescribe monitoring the wear morphology to optimize the machining parameters to achieve the best tool life [87–89]. There are different wear morphologies, and some of them are desired, and others are undesired morphologies. To achieve the maximum tool life, the desired wear morphology must prevail. The desired and undesired wear morphologies are discussed in Section 4.2. The decision based on the wear morphology also helps the tooling engineers generalize their knowledge across different tool geometry, coating grades, and working materials. The tooling engineers are taught to troubleshoot tool life using the wear morphologies, and the remedy to those wear morphologies [87–90]. This helps the tooling engineers generalize their knowledge.

In this study, the authors take the approach a tooling engineer takes to optimize the machining parameters based on the visual information available. A tooling engineer first looks at the tool for the type of wear and approximates the level of wear based on this evidence the engineer changes the parameter appropriate for the level of wear and type of wear. These appropriate changes are relative to the initial machining parameters, and the decision of the magnitude of changes in parameters is a skill developed over the years by the engineers. The presented study replicates this decision making through an autonomous system that first recognizes the type of wear, then the level of recognized wear is measured, and finally, the skills are captured in the system through fuzzy logic rules. Thus, performing the task of tooling engineer autonomously and independently. This autonomous decision-making system equips the new inexperienced machine operators with the preemptive remedy actions to achieve full utilization of the tool life. Also, the system can be used in fast-tracking of identification of the best machining parameters for new exotic materials. With the full integration of the proposed system with the machine controllers, the study can contribute to the concept of lights out machining without the need for human intervention.

The contribution of the study is a fuzzy controller that replicates human decision making when it comes to machining parameter optimization with tool life as the objective. The detection of wear morphology and measured values of the detected wear morphology serve as feedback to the controller, thus makes the proposed system a closed-loop system. This approach also helps in generalizing the system across different working materials, tool geometries, and tool grades as the decisions are based on visual evidence of wear morphology.

The rest of the chapter is structured as follows. The background literature is discussed in Section 4.2. In Section 4.3, the methodology is proposed starting with the overview followed by the basic concepts used in the system. In Section 4.4, the case study and the results are demonstrated. Finally, the further development needed in the full deployment of the system and the conclusions are given in Section 4.5.

4.2 Machining parameters optimization literature review

Optimization of machining parameters is one of the extensively studied fields of manufacturing, but the objectives of the optimization have been different in different studies. Surface finish [20–25] is one of the primary objectives to optimize the machining parameters where inputs to prediction models are cutting speed, feed and depth of cut, among others, and the model is expected to predict the surface finish. The effects of various parameters on power consumption [24] are also studied extensively to provide the best working parameters that consume the least power. Cycle time or production time [26] and Manufacturing cost [81, 82] are also a common objective to optimize the cutting parameters. Other than the above-mentioned objectives, some studies have also considered cutting force or load on machine [24], and material removal rate [27] as the objective to optimize the machining parameters. A complete review of different optimization objectives can be found in the study done by Rana et al. [91].

The machining parameter optimization objectives mentioned in the previous paragraph are essential as they affect machining quality and production cost. On the other hand, if surface finish, power consumption, and production cost are considered without considering tool life, the manufacturers run the risk of underutilizing the tool or, in the worst-case, end up using the wrong tool, which drives up the tooling cost. Therefore, there is a need for a system that can optimize the tool life. In the context of optimized tool life, if the other desired outcomes like surface finish, production time, and cost are not achieved, the tool selection is wrong and must be changed in consultation with tooling engineers.

The parameter optimization study has used a variety of methodologies to achieve the desired objectives. Artificial Neural Network (ANN) is one of the new methodologies used in the last decade [24]; this methodology establishes the nonlinear relations between the input variables and target variables. The relation later helps in the prediction of outcomes of using individual machining parameters combinations. The genetic algorithm [92] is also a commonly used methodology based on the basic principle of selection of the best solution to the optimization problem. Experimentation, which involves trying different parameters and determining the best paraments of the lot, is also a common approach; the Taguchi method [22] is used to design these experiments. In the experimentation approach, which forms the basis of the above-mentioned methodologies, there is no room for a closed-loop system, which can adjust the parameters based on the online feedback from the change in a machining environment. The experimental approaches are also limited to the material they are experimenting with or the tool geometries that are used in the studies. If the material or the tool geometry or the tool coating grade changes, the assumptions make the generalization of the findings for a different material or tool impossible.

The proposed system develops a feedback loop and a closed system by optimizing the parameters based on the wear condition of the tools. The wear on the cutting tool is unavoidable. There are, however, desired and undesired wear patterns. The desired wear morphologies must prevail for the full utilization of cutting tools. Abrasion wear is the removal of small fragments [28] from the tool, which relatively preserves the rake angles of the cutting tool, giving the best life designed by the manufacturer. The abrasion wear pattern is also termed as normal flank wear by the tooling engineers. The other wear mechanism is plastic deformation, which significantly changes the working angles [28] of the insert rendering it unfit for machining in a short cutting time, this type of tool wear is commonly seen while machining high melting point material at high cutting speeds. The adhesive wear pattern is the other commonly seen wear pattern in the cutting insert, where the material being cut adheres to the cutting edge and the rake face [28], this leads to change in cutting angles and poses a risk to smooth chip flow which makes the tool unfit for machining, Built-Up Edge (BUE) is the industrially used term for this kind of wear pattern. Considering that the plastic deformation and adhesive wear patterns drastically reduce the usability of the cutting tools, tool manufacturers prescribe remedy actions to achieve abrasive wear pattern, that is ideal wear pattern to realize the full life of the cutting tool. The remedy actions to achieve abrasion wear patterns are discussed later in Section 4.3.3.

Parameter optimization based on TCM can be done using indirect and direct monitoring methods [93]. Indirect methods use data from one or more of vibration [8–10], sound [7], and force [8] sensors. On the other hand, direct methods rely on first-hand evidence, like images of tools [11]. While indirect methods are online systems and give information on real-time bases, they are less accurate and susceptible to noise when the systems are deployed in machine shop floors [12]. Indirect systems are also trained for predictions based on specific experimental data provided by the sensors, and the model needs to be retrained if any of the parameters in the experiment change. For example, if the vibration sensor-based model is trained for finishing geometry, the same model can not be used if the geometry changes to roughing geometry as the vibration levels are higher for roughing geometry; the same can be implied for other indirect methods. Direct systems like vision-based systems are not real-time systems but are in process systems; they can be designed to work in between cycles [13] and tool change programs. Since direct systems are based on first-hand evidence, they present the advantage of higher accuracy. Also, the vision systems can be placed away from the metal cutting this allows them not to interfere with machining operations, that is why vision systems have gained popularity in inspects [94], collusion detection [64, 65], and other applications. Direct systems can also be trained to monitor wear morphologies, which have specific remedy actions to achieve desired wear morphology. These remedy actions are common to different tool geometries, coating grates and workpiece materials. The ability to work with wear morphologies allows the system to generalize the remedy rules for different applications. Considering Higher accuracy of direct methods, combined with the ability to generalize remedy rules the computer vison based direct method is selected to create a feedback loop for a closed machining parameter optimization system, that can respond to change in tool condition.

The gap in machining parameter optimization in the context of tool life is an area with scarce publications. It is evident in the literature discussed in the previous paragraphs; the proposed system is designed to address this gap. The developed system is a combination of a Convolutional Neural Network (CNN) and Fuzzy Logic (FL) methodology. The previous studies use FL for TCM [95, 96], but FL is not the best approach for feature recognition since the feature descriptions have to be hardcoded in terms of fuzzy rules which takes a considerable amount of computational memory and also FL systems can not accommodate new situations not bound by the rules [97]. In this regard, CNN approaches are more accurate and also do not require the feature definition stage [61], This expedites the training process and also improves the ability to recognize a variety of wear morphologies. FL, however, is efficient in converting human knowledge into variables that computers can understand [97]. The FL in the proposed methodology is used to model the expert and tool manufacturer's troubleshooting knowledge. The proposed hybrid system uses CNN as the feedback and FL as the controller, which selects and adapts the machining parameter.

4.3 Hybrid Fuzzy controller with an image feedback system

The overview of the proposed fuzzy controller can be seen in Fig. 4.1. The proposed system is divided into the controller and the feedback sections. The feedback section consists of the wear classifiers that classify the type of wear on the tool, and the approximates amount of wear on the tool. The type of wear, amount of wear, the component diameter, and spindle revolutions per minute (RPM) form the inputs to the controller; this is further elaborated in Section 4.3.1. The first step in the controller is the fuzzification, where the change in cutting speed, wear type, and lever of wear are converted to linguistic variables discussed in Section 4.3.2. In Section 4.3.3, the rule base, which forms the intelligence of the controller for remedial actions as suggested by tooling engineers and tool manufacturers, is developed. The output of the controller is a crisp number that is used to control the cutting speed of the machine. The output of the system is a remedial action to achieve desired wear morphology that improves tool life. The process of relying on the evidence of wear morphology, amount of wear, and the initial machining parameters replicate the tooling engineer decision-making process when it comes to machining parameter optimization. The techniques of output inference and defuzzification are discussed in Section 4.3.4.

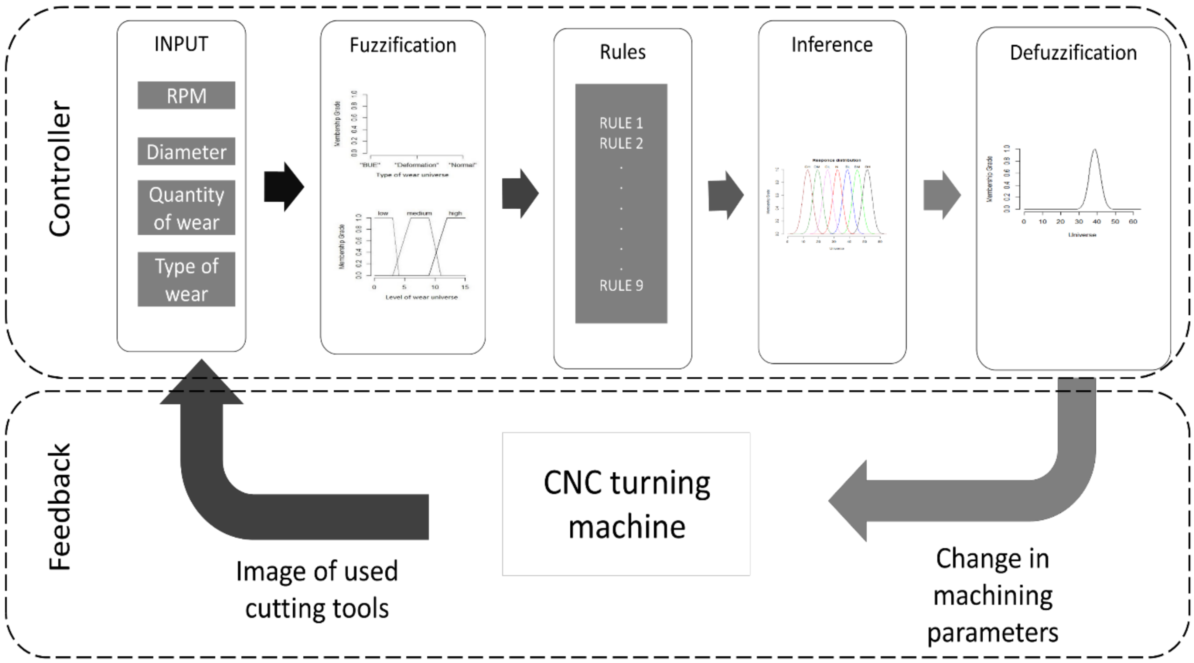


Fig. 4.1 Overview of the fuzzy controller.

4.3.1 Inputs to controller

The controller uses four inputs diameter of the component, RPM, type of wear, and level of wear. The cutting speed (V_c) in meters per minute is calculated using Equation 1 [98], where D is the diameter of the component to be machined in millimeter, and N is RPM of the workpiece.

$$V_c = (\pi DN)/1000 \tag{1}$$

There have been many studies in wear type identification and wear amount estimation fields. Sun and Yeh [16] developed image processing methodology that can recognize the type of wear, and the level of wear is estimated by accounting for the number of pixels in the wear region. Wu et al. [61] took a neural network approach to identify the type of wear pattern and used a minimum circumscribed rectangle to get the quantity of the wear. The proposed system uses a neural network approach to identify the type of wear automatically by capturing the images of the used tools, and the amount of wear is manually calculated. However, there are other technologies developed that can also automate the amount of wear calculation.

Neural networks are one of the most used methods in image recognition. The neural network allows for automatic feature extraction by learning the nuanced differences in the images. The images are manually classified into different wear categories and are used to training and validate the classification models. Once the training is complete, the model can automatically identify the different wear patterns by uploading the new images.

The CNN architectures use different layers which perform different actions on the images. The convolution layers, narrow down on the region of interest and create useful descriptions of the images which make them best suited to work with images [70]. The output of the convolution layers then passes through the pooling layer, which in the case of the proposed architecture is a max-pooling layer which reports the maximum value in the predefined image pixel neighborhood. Max pooling layers make the proposed architecture more robust against small translation in image pixel data [77]. The dense layers are the fully connected layers where each neuron is interacting with all the neurons of the previous layers. [78]. The last dense layer has the same amount of neurons as the number of wear classes, the output of the layer is the network's prediction for the image belonging to three classes, this is summarized in Equation 2 where y_p is the prediction of the model.

$$y_p = \begin{cases} 0 & \text{if the image has BUE} \\ 1 & \text{if the image has deformation} \\ 2 & \text{if the image has normal wear} \end{cases} \tag{2}$$

Activation functions are commonly used in the neural network to allow them to accommodate and learn non-linear functions [77], Rectified Linear Unit (ReLU) is commonly used in hidden layers of the network architectures as they return zero gradient values of negative nodes and the node value for positive inputs this prevents the gradiaent from becoming too small and in process improve the ease of computation [99]. The softmax activation function is used in the final layer to represent probability distribution over different classes, which is a common practice in classifier architectures [77].

The parameters are where the intelligence of the layers are stored in terms of weights. These weights are fine-tuned by backpropagation in the training process. The model uses categorical cross-entropy as loss function [77] and ADAM as the optimizer for training and optimizing the weights[78]. More information about the training and optimization neural network architectures can be found in [61, 77, 78, 99, 100]. The proposed system uses the CNN architecture proposed in Table 4.1 to classify the wear type.

Table 4.1 CNN architecture for wear type classification model.

	Layer type	Input Shape	Output Shape	Activation function	Parameters
1	Convolution layer	200,200,3	198,198,32	ReLU	896
2	Max pooling layer	198,198,32	99,99,32		0
3	Convolution layer	99,99,32	97,97,32	ReLU	9248
4	Max pooling layer	97,97,32	48,48,32		0
5	Convolution layer	48,48,32	46,46,64	ReLU	18496
6	Max pooling layer	46,46,64	23,23,64		0
7	Convolution layer	23,23,64	21,21,64	ReLU	36928
8	Max pooling layer	21,21,64	10,10,64		0
9	flatten (Flatten)	10,10,64	6400,1		0
10	Dense layer	6400,1	50,1	ReLU	320050
11	Dense layer	50,1	35,1	ReLU	1785
12	Dense layer	35,1	10,1	ReLU	360
13	Dense layer	10,1	3,1	Softmax	33

The amount of wear is manually demarcated on the images of the used tools, although the magnitude can also be automatically generated by technologies discussed in [16, 61, 101], and many other studies, this work is not replicated. The type of wear (y_p), amount of wear in terms of micrometers, and cutting speed (V_c) form the inputs to the fuzzy controller.

4.3.2 Fuzzification

There are two variables, type of wear χ_T and the amount of wear χ_A which form the input to the fuzzy systems. $\mathcal{L}_T = \{\text{"BUE," "Deformation," "Normal wear"}\}$, and $\mathcal{L}_A = \{\text{"Low," "Medium," "High"}\}$ are the family of linguistic values for the type of wear and amount of wear, respectively. L_T is the label used from family $\mathcal{L}_T$ and L_A is the label used from family $\mathcal{L}_A$ this is summarized by Equations 3 and 4.

$$L_T = \begin{cases} \text{BUE} \\ \text{Deformation} \\ \text{Normal wear} \end{cases} \tag{3}$$

$$L_A = \begin{cases} \text{Low} \\ \text{Medium} \\ \text{High} \end{cases} \tag{4}$$

The amount of wear has trapezoidal membership function [102]; this is summarized in Equation 5, where x_a is the measured value of wear on the cutting tool in micrometers. The different values of p, q, r, and s boundary points are summarized in Table 4.2. The pictorial representation of the wear type and amount of wear is shown in Fig. 4.2a and Fig. 4.2b, respectively, where the values on the x-axis in Fig. 4.2b are the micrometers of wear on the cutting tool. Similarly, for the type of wear, the membership function is singleton given in Equation 6, where $x_0 = y_p$.

$$\mu_A(x_a;\ p,q,r,s) = \begin{cases} 0 & x_a \le p \\ (x-p)/(q-p) & p < x_a \le q \\ 1 & q < x_a \le r \\ (s-x)/(s-r) & r < x_a \le s \\ 0 & x_a > s \end{cases} \tag{5}$$

$$\mu_T(x_T; x_0) = f(x) = \begin{cases} 1 & x_T = x_0 \\ 0 & x_T \ne x_0 \end{cases} \tag{6}$$

Table 4.2 Boundary points for wear amount membership functions.

A_x	p	q	r	S
Low	10000	200	300	400
Medium	350	600	900	1100
High	900	1200	1500	10000

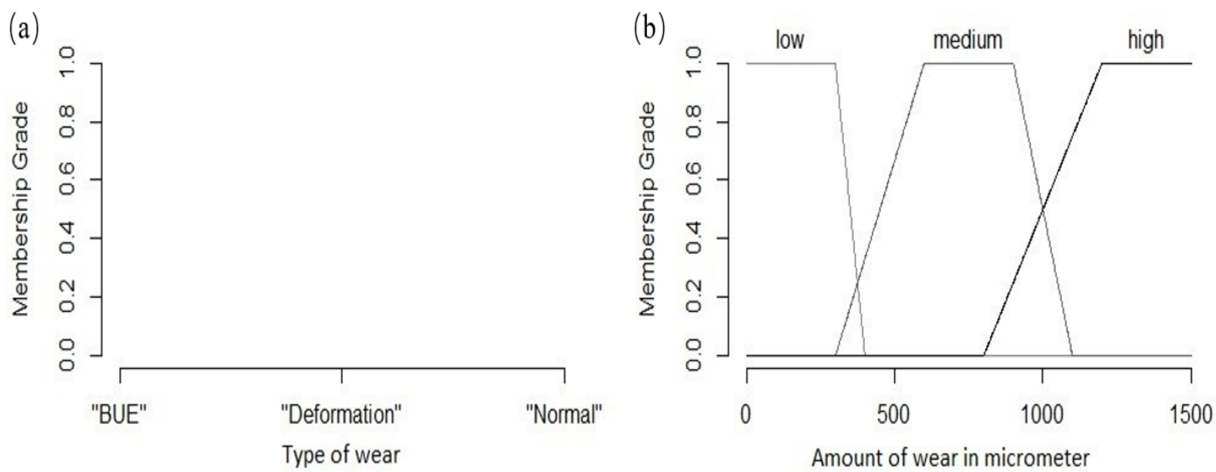


Fig. 4.2 Linguistic input variables a) type of wear b) amount of wear.

The response ($\Re$) is divided into seven linguistic variables $\mathcal{R}$. Where, $\mathcal{R}$ = { Deformation High (DH), Deformation Medium (DM), Deformation Low (DL), Normal (N), BUE High (BH), BUE Medium (BM), BUE Low (BL)}. R is the label used form family $\mathcal{R}$. The Gaussian membership function [102] for response variable (μ_R) is given in equation 7. The c and s values for R are summarized in Table 4.3. Where c is the mean of the distribution, s is the standard deviation, and y is the output value. The mean of the linguistic response variables is dependent on the initial cutting speeds.

$$\mu_R\,(y; c, s) = e^{\left(-\frac{(y-c)^2}{2s^2}\right)} \tag{7}$$

Table 4.3 Mean and standard deviation values for different response linguistic variables.

R	c	s	R	c	s
BH	$V_c + (0.6\ V_c)$	3	DL	V_c - $(0.2\ V_c)$	3
BM	$V_c + (0.4\ V_c)$	3	DM	V_c - $(0.4\ V_c)$	3
BL	$V_c + (0.2\ V_c)$	3	DH	V_c - $(0.6\ V_c)$	3
N	V_c	3			

4.3.3 Rules

The rules for the fuzzy controller are developed using the knowledge base of troubleshooting guides from different tool manufacturers. The different statements extracted from troubleshooting guides are given in Table 4.4. The troubleshooting guides only suggest the overall remedy actions, but the magnitude of change in cutting speed or the feed rate is the skills developed by tooling engineers over time and experience, these skills are captured in the fuzzy rules.

Table 4.4 Remedy actions from knowledge base troubleshooting guides published by tool manufacturers.

Wear mechanism detection	Remedy statement for cutting speed	Reference	Remedy statement for feed rate	Reference
BUE	Increase cutting speed	[87, 88, 103]		
Normal wear	Desired wear pattern	[89, 90, 103]	Desired wear pattern	[89, 90, 103]
Deformation	Decrease cutting speed	[87, 88, 103]	Decrease feed rate	[87, 88]

Based on the information from the knowledge base and the tooling engineer's skills, the fuzzy rules ($\mathcal{H}^i$) are developed, the basic fuzzy rule is given by Equation 8. The different linguistic values of L_T, L_A, and R for rule i are summarized in Table 4.5. The fuzzy rules model the expert statement, for example, rule 1 states that if the wear type is “BUE” and wear amount is “High” then increase the cutting speed by “BH,” where “BH” is the increase of 60 percent of initial cutting speed.

$$\mathcal{H}^i = \{\text{IF} \quad \chi_T \quad \text{is} \quad \mathrm{L_T} \quad \text{AND} \quad \chi_A \quad \text{is} \quad \mathrm{L_A} \quad \text{THEN} \quad \mathfrak{R} \quad is \quad \mathrm{R}\}_{\mathrm{i}=1}^{9} \tag{8}$$

Table 4.5 Linguistic variables for different fuzzy rules.

i	L_T	L_A	R
1	BUE	High	BH
2	BUE	Medium	BM
3	BUE	Low	BL
4	Normal	High	N
5	Normal	Medium	N
6	Normal	Low	N
7	Deformation	Low	DL
8	Deformation	Medium	DM
9	Deformation	High	DH

4.3.4 Inference and defuzzification

Mamdani-Assilan fuzzy inference method is used for fuzzy inference. This method is suitable for the application at hand as it can work with the conjunctive interpretation of fuzzy rules in the canonical form given in Equation 8 [102]. The conjunctive “AND” is interpreted as the minimum ($\wedge$) [102]. The inference results from each rule are finally added using maximum ($\vee$) operation [102]. The final inference value $\mu_{R^*}(y)$, which gives the area under all the triggered rules is given in Equation 9.

$$\mu_{R^*}(y) = \vee_{i=1}^{9} \left[\mu_T^i(x_T) \quad \wedge \quad \mu_A^i(x_A) \quad \wedge \quad \mu_R^i(y) \right] \quad y \rightarrow \mathbb{Y} \tag{9}$$

The defuzzification is done using the center of gravity (COG) method [102] where the crisp number for new cutting speed y_{new} is returned by the controller. The COG of the aggregate area of all the rules represented by Equation 9 is calculated using Equation 10. y_{new} is the new cutting speed used for the new machining cycle, which is influenced by initial cutting speed, type of wear, and amount of wear detected on the tool, used in the previous cycle.

$$y_{new} = \frac{\int_{\mathbb{Y}} y \quad \mu_{R^*}(y) \quad dy}{\int_{\mathbb{Y}} \mu_{R^*}(y) \quad dy} \tag{10}$$

The fuzzy controller developed can only work with the cutting speed. Similarly, the fuzzy controllers can be developed for other machining parameters like feed rate and depth of cut. Cutting speed was considered as there is a consensus among the previous studies that the cutting speed is one of the most influential factors when it comes to tool life [104–106].

4.4 Hybrid Fuzzy controller case study

The case study started with the training and deployment of wear classification CNN. For the training, first, the images of used cutting tools that have BUE, deformation, and normal wear patterns are acquired using a GigE DFK 33GP006 image sensor with TCL 3520 5MP lens with a 35 mm focal length; the setup can be seen in Fig. 4.3. The examples of images from different categories can be seen in Fig. 4.4. The image sensor has a resolution of 2592 * 1955. The neural network models were built and trained in the Intel Core i5 processor using the Tensorflow backend and Keras higher level package. For the wear classification model, a total of 207 images were used to train the model discussed in Table 4.1, and 89 images were used for validation of the model. The images, when captured, were of different sizes but were resized to 200*200*3 RGB images using the EBImage [107] package.

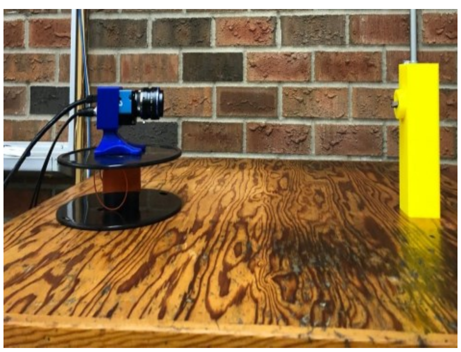


Fig. 4.3 Image capturing setup.

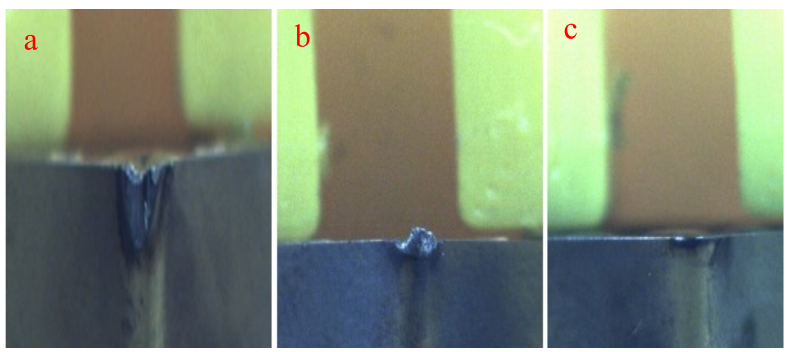


Fig. 4.4 Examples of 200 x 200 pixels image for a) Deformation, b) BUE and c) Normal wear

The confusion matrix of wear type classification model's predictions on the validation data set is shown in Table 4.6. The model has 86.52 percent accuracy and 0.3752 loss on the validation data set. The confusion matrix illustrates that the model performed reasonably well in identifying the wear patterns; the numbers in the diagonal of Table 4.6 are the correct predictions.

Table 4.6 Base model confusion matrix.

Actual label / Prediction label	BUE	NORMAL	DEFORM
BUE	20	2	0
NORMAL	3	27	1
DEFORM	1	5	30

The wear classification model is then deployed using a Graphical user interface (GUI). The GUI asks the user to upload the image of the used tool, and the output is the type of wear, this is manually fed to the fuzzy controller. The example of the deployed GUI can be seen in Fig. 4.5. The amount of wear can be automatically measured using various technologies discussed in Section 4.3.1; however, in the proposed system, the measurement is done manually using IC Measure software [108]. The examples of the measurements can be seen in Fig. 4.6.

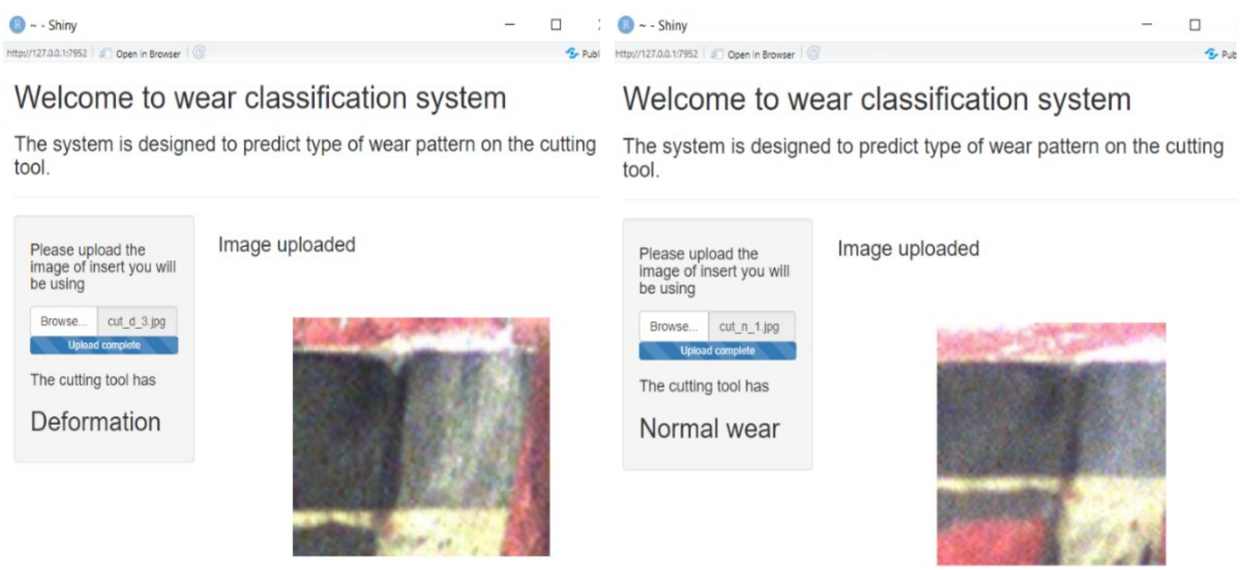


Fig. 4.5: GUI for the wear classification model.

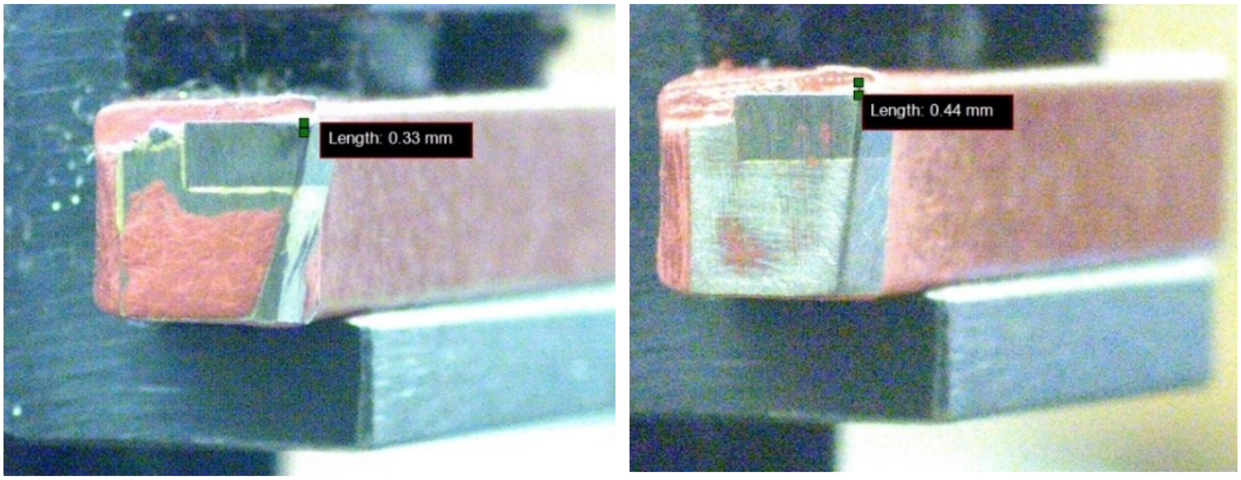


Fig. 4.6 Amount of wear measurement using IC Measure software.

For the fuzzy controller evaluation, Micro-Mark mini-lathe 7x16 is used for machining. The tools used are uncoated high-speed steel tools. The workpiece material is Stainless steel 304. The cutting speed was monitored by recording the diameter of the component and the RPM (measured using REED instruments R7050 photo tachometer and counter). The standard operating procedure in Table 4.7 was followed for collecting the data; the steps are repeated after every cut of 78mm.

Table 4.7 Standard operating procedure for collecting data.

Step 1: Start the rotation and set the RPM to a predetermined level, as indicated by the fuzzy controller.
Step 2: Carry out the metal cutting using automatic leadscrew feed.
Step 3: Capture the image of the used tool and record the wear detected by wear classification GUI.
Step 4: Measure the wear on the tool using IC Measure software if the wear is BUE or Deformation.
Step 5: Record the diameter of the workpiece after the machining.
Step 6: Input the diameter, RPM, type of wear, and measured wear to the fuzzy controller.
Step 7: Record the cut number, cutting speed, and RPM suggested by the fuzzy controller.

The data is collected for four cutting edges; the result of the experiment is shown in Annexure b and summarized in Fig. 4.7. Tool 1 and Tool 3 are initiated with abnormally low (23 m/min) and high (39 m/min) cutting speeds, respectively, which generated BUE and Deformation. The use of tools is stopped when the undesired wear patterns are detected. The life for Tool 1 and Tool 2 in terms of contract length is 312mm and 234mm, respectively. When the undesired wear patterns are detected, the fuzzy controller suggested the change in cutting speed, when the suggestion is used while machining with Tool 2 and Tool 4, the tool life improved by more than 100 percent as shown in Fig. 4.7.

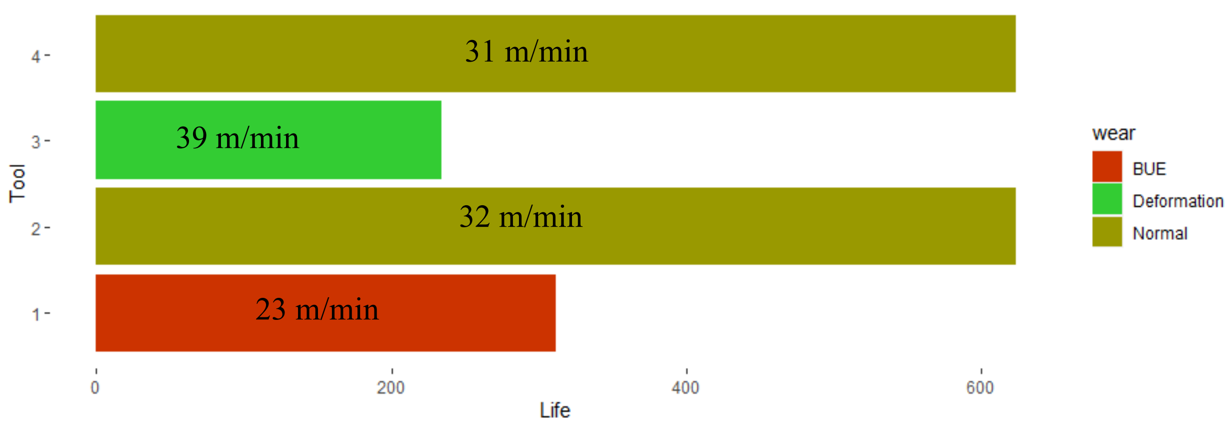


Fig. 4.7 Consolidated results from the experimental data presented in Annexure b.

The study illustrates the ability of the system to detect different wear morphologies and take remedy actions by changing the cutting speed to achieve the desired wear patterns and, in this process, achieve better tool life. The system can work with different materials and tool geometries as the remedy actions are based on the wear morphologies. The system was evaluated on a manual lathe, which did not allow for the control of feed rate. Similar fuzzy rules, as discussed in section 4.3.3, can be developed for remedy actions that involve controlling feed rates to achieve desired wear patterns. The study only discusses BUE and Deformation as undesired wear patterns. However, there are other undesired wear patterns like chipping, crater wear, among others, which have different remedy actions. There is a need to further develop the system to work with other wear patterns. There is also a need to make the system completely automatic by integrating the outputs of the wear classification model, wear amount measurement tool with the input to the controller, this process in the proposed study is done manually.

4.5 Conclusion

Machining parameter optimization is one of the extensively studied fields of manufacturing, with the objective of optimization being different. The proposed system uses the theory of wear mechanism to optimize the machining parameters. The objective of the study is to get the desired wear pattern when undesired wear patterns are detected to achieve better tool life. This problem is divided into two sections first, the detection of wear mechanism and level of wear, and in the second section, these detections are used as signals to trigger fuzzy rules, which change the machining parameter to obtain the desired wear pattern in the next cutting edge. The system uses CNN for the detection of wear mechanisms. The fuzzy controller uses the output of wear classifier, amount of wear, and current state of machining parameters as input to suggest changes to the machining parameters for the next cutting edge. The case study developed illustrates that when the suggested changes are incorporated, the tool life can be improved by 100 percent. Since the system is dependent on the wear morphology as feedback to the deployed parameters, the system is not limited by the working material or tool geometries.

Chapter 5: TCM framework for threading and grooving tools

In the previous chapters, we defined the definition of TCM and also developed new systems that utilize the TCM to achieve different objectives like quality and machining parameters optimization. TCM, in case of forming tools, however, is different. The heave depth of cuts and feed rates [109], which forming tools like threading tools and grooving tools take, expose different faces of the tool to the workpiece. Therefore there is a need to monitor three faces of forming tools. In this chapter, a methodology that uses three-dimensional descriptions of tool and feature extraction capabilities of neural networks to classify images of the forming tools like threading and grooving tools based on the wear morphology is proposed and validated using synthetic data. The algorithm is designed to generalize across wear patterns as it doesn't need any qualitative or image processing input.

5.1 Introduction

Machine-shops around the world are moving towards Industry 4.0 [56], the equipment in the machine-shops are gaining the ability to self-manage their activity [68, 110, 111] hence it is critical to look at TCM and product quality through machining tending prism. There is enough literature to demonstrate mechanical and vision capabilities [112], [113], but there is a need to develop the artificial intelligence and control systems for fully autonomous machine tending capabilities [6] as presented in "lights out working" case study in [4]. In view of these developments, research related to the Autonomous Quality Management and Control Program (AQMCP) has taken a central stage. Tool condition self-management is part of AQMCP, the loss due to rejection of machined parts is not limited to rejected workpieces but also to the allocated opportunity cost related to the human and machine time spent to work the rejected workpieces [36]. Since the tool on the machine is consumable, monitoring their condition becomes vital and prerequisite to manage production cost [15] and production quality [114]. Traditionally the machine operator has been the single source of information used to measure tool condition [115]. Lately, with the advancement in sensors and visual systems, the TCM has been modified to some extent, the complete review of which can be found in [59]. The TCM is classified into indirect and direct methods [62]. While indirect methods are online measurement systems and provide feedback on a realtime basis, direct methods are more accurate [59] and try to replicate the human monitoring process [52]. Hence the proposed methodology uses direct methods, considering the advantages it provides and enough time between machining cycles in a practical setting to determine the condition of the tool.

TCM in case of form tools like threading cutting and grooving tools have different requirements when compared to a single-point cutting tool. In forming tools, all the faces of the tool come in contact with the workpiece due to the large depth of cuts [116]. The undesired wear in these forming tools result in imperfections like feed marks and chatter marks, which might lead to operational failure of the components [116]. Therefore, it is imperative that the TCM in the case of form tools takes the three-dimensional view before determining the condition of the tool.

The proposed framework combines the concepts of machine tending and TCM for forming tools. The proposed system classifies the type of wear pattern, considering the three-dimensional description of the tools. The methodology takes inspiration from the previous study done by [16, 19, 52]. Lanzetta starts with the classification of the tool based on the wear morphology and then takes a quantitative approach based on the parameters like the width of flank wear and crater wear, among others. Sun and Yeh [16], designed, and implemented the visual hardware system and used image processing and filtering techniques to determine the wear patterns. The disadvantage of this technique is that it needs different filters and transformation principles of image processing for identifying different types of wear. Wu et al. [19] developed a neural network-based system for tool wear detection and estimation. The ability of the neural network to automatically extract and learn the wear features provides the advantage of skipping the feature extraction step, which is necessary for other approaches. Hence the proposed methodology provides a framework using feature extraction capabilities of the densely connected deep neural networks (DNN) [117] to work with raw image data, and which requires, no qualitative inputs or image preprocessing functions and which can be easily replicated for the purpose of wear morphology classification for Built-Up Edge (BUE), Edge Deformation (ED) and abrasion wear, also known as normal wear (NOR) as seen in Fig. 5.1. The aforementioned systems, however, are not suitable to be implemented in TCM of forming tool as they do not consider the damages, large depth of cuts can impose on different faces of the tool, considering this a TCM system based on a three-dimensional description of the tool is proposed.

5.2 Neural network methodology for wear type classification

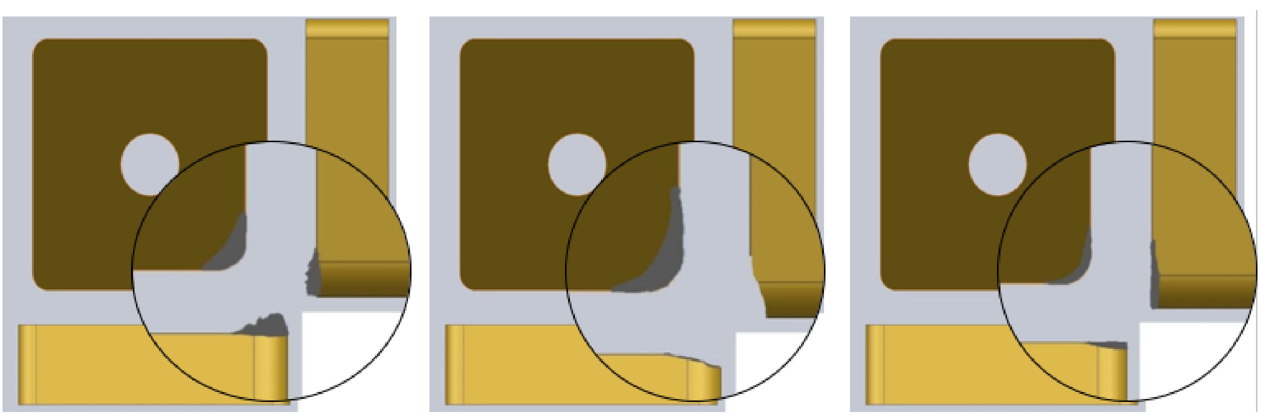


Fig. 5.1 left image is BUE wear pattern image, middle image is edge deformation wear pattern and right image is normal wear pattern

DNN, also called as multilayer perceptrons is a black-box model where we are trying to estimate a function $f^{\star}(\mathbf{x})$ that best resembles the actual function $f(\mathbf{x})$ [77]. The random variable y represents the category or wear, which can take three possible values. Equation 1 is the actual function that maps the pixel data to y. Equation 2 is our estimation of the actual function, where θ is the parameter estimated given the data $\mathbf{x} = \{x_1, x_2, x_3 \dots, x_a\}$. In the proposed framework, y_t is the target label for the picture and y_p is the prediction from the neural network for the picture, and the $\mathbf{x}$ is the pixel values from the image, where $a = 30000$.

$$y = \begin{cases} 0 \text{ if wear is BUE} \\ 1 \text{ if wear is ED} \\ 2 \text{ if wear is NOR} \end{cases}$$

$$y_t = f(\mathbf{x}) = f(x_1, x_2, x_3 \dots, x_a) \tag{1}$$

$$y_p = f^{\star}(\mathbf{x}; \theta) = f^{\star}(x_1, x_2, \dots, x_a; \theta) \tag{2}$$

Fig. 5.2 gives the architecture of the neural network used in the classification. This architecture is finalized after careful tuning. Each node in the network acts as a linear aggregator, where it takes in the inputs from the previous layer multiplies it with the weights (strength of synaptic links) aggregates the product and then transforms with a non-linear activation function [77, 118, 119]. This is summarised in equations 3 and 4. $\mathbf{w}_{a,b}$ in equation 3 is the weight of synaptic link, i is layer of the network, j is the node in layer i, n is number of nodes in layer i-1 and φ is nonlinear activation function.

$$H_{i,j} = \sum_{a=1}^{n} \mathbf{x}\mathbf{w}_{a,b}^{T} \tag{3}$$

$$h_{i,j} = \varphi(H_{i,j}) \tag{4}$$

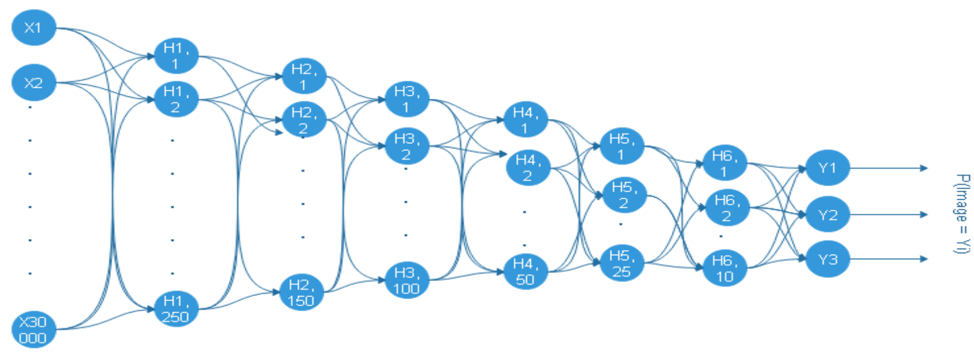


Fig. 5.2 DNN architecture used for insert wear morphology classification

The activation function φ used in the hidden layers is a rectified linear unit (ReLU) and softmax for the output layer. ReLU summarized in equation 5 is used in the hidden layer as it makes the optimization process easy [77]. Softmax summarized in equation 6 gives the probability distribution of y_p over c possible classes [77].

$$h_{i,j} = \max\left(0, H_{i,j}\right) \tag{5}$$

$$y_p = \frac{e^{Y_p}}{\sum_{c=1}^{3} e^{Y_c}} \tag{6}$$

The optimizer and loss functions used were Adam and categorical cross-entropy, respectively. Adam was selected as it uses adaptive momentum [77], and because it is more efficient than other optimizers and gives better results with fewer iterations, the details of Adam algorithm can be found in [78]. Equation 7 provides the cross-entropy loss function optimized by the Adam algorithm.

$$\text{loss} = -\sum_{c=1}^{m} y_{t,c} \log\left(y_{p,c}\right) \tag{7}$$

The parameters used in Adam optimizer were learning rate = 0.001, the beta^1 = 0.9 and beta^2 = 0.999. The validation batch split of 30% was used, the training was terminated at the 50th epoch as the model stabilized; accuracy is used as the metrics for evaluation.

5.3 Three dimensional data-preparation

Fig. 5.3 is a flowchart that gives an overview of the entire classification method. The data set consists of one hundred thirty-five synthetic image data points, which are then combined to get forty-five images with fifteen images belonging to BUE, NOR, and ED wear patterns, as seen in

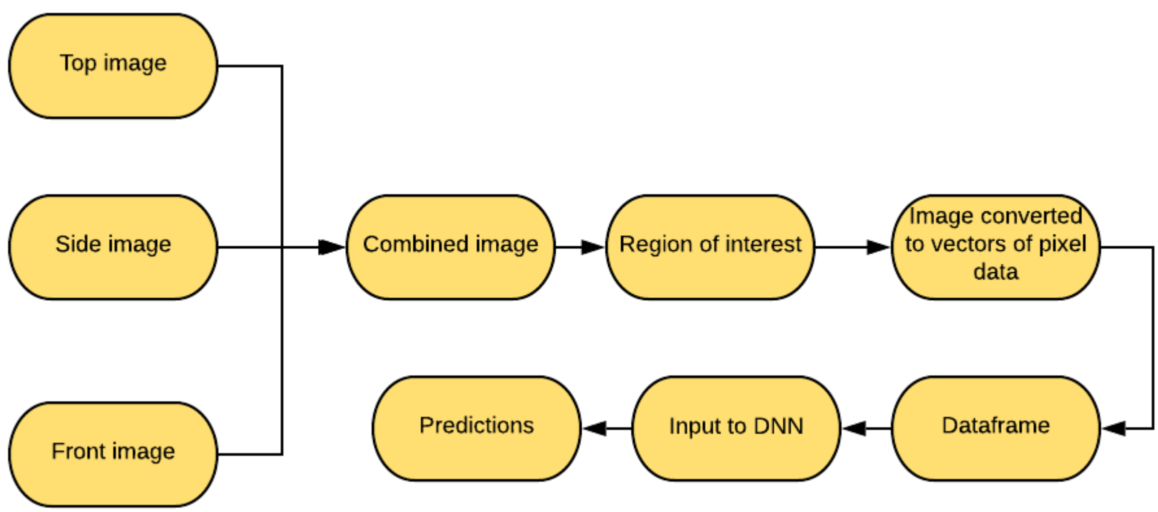


Fig. 5.3 Flow chart for insert wear classification method

Fig. 5.1. The data set is then partitioned randomly to get fifteen images for testing the DNN; this set is not used in the training of DNN. Then the image is localized to a region of interest by a simple automatic zooming algorithm that concentrates on the working tip of the insert. The image

at this stage is of size [100, 100, 3], where [100, 100] are the width and height of the picture, and 3 refers to the RGB channels of the image. Each image is then converted to a one-dimensional vector with dimension [30000, 1], then the rows are combined to one data frame where each row is an image, and the columns represent the pixel data [18], the vector then forms the input to the neural network. These inputs are then multiplied with free parameters $w_{a,b}$ the process is repeated for all the hidden layers. The output layer of the neural network has three nodes, which give the probability of the image belonging to BUE, ED, or NOR wear. The most significant probability is assigned as the prediction label for the picture.

5.4 Forming TCM framework results and discussions

Fig. 5.4a gives an increase in accuracy for different iterations. Fig. 5.4b presents the loss function, which presents the magnitude of the difference between the prediction and the actual value. After fitting the model, it was tested for a new data set that was not used for training or validation. The model performed reasonably good with 93.33 percent accuracy on the test dataset.

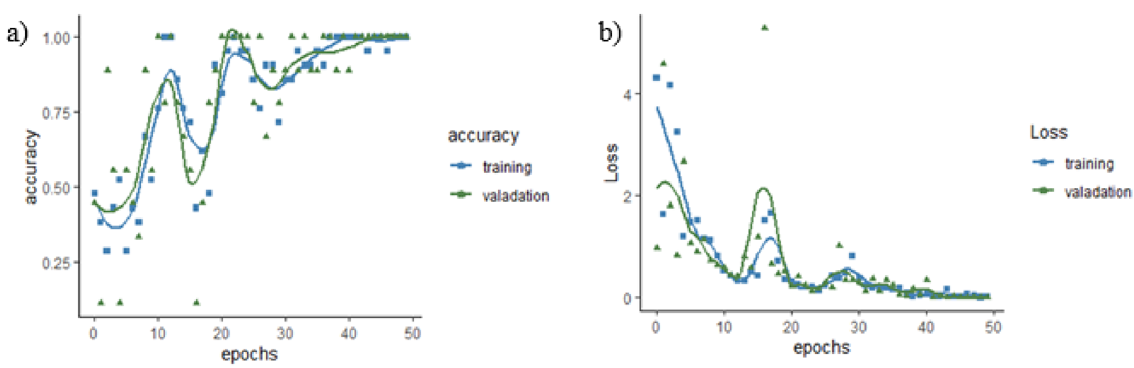


Fig. 5.4 a) Accuracy of wear classification neural network for 50 epochs. b) Loss of wear classification algorithm for 50 epochs

A Processor with Intel i5 and 12GB RAM was used for training and testing the model. The confusion matrix for the test data result can be seen in Table 5.1. As illustrated in the confusion matrix, only one image was miss classified as NOR wear when the actual wear pattern was ED.

Table 5.1 Confusion matrix for the wear classification model.

Actual label / Prediction label	BUE	ED	NOR
BUE	3	0	0
ED	0	6	0
NOR	0	1	5

A software architecture for TCM specific to forming tools is proposed. The proposed system used synthetic data for evaluation. In the future study, a station for extraction of a three-dimensional description of the cutting tool is to be developed and deployed on the CNC machine.

5.5 Conclusion

A framework which uses raw image data with no quantitative inputs or image processing techniques that can be generalized to different types of wear pattern is proposed. Three-dimensional representation of the inserts is used to train the model, and this is explicitly targeted for forming tool condition monitoring. DNN architecture is tuned to give the best results for the classification using adam optimizer; this architecture is capable of extracting underlying features of the images and is used to determine the useability of the tool. This intelligent framework is the first step in tool-related machine tending, which will be implemented in the vision-based systems, which takes the pictures of the inserts when it is in the CNC machine pocket, waiting for the next cycle to start.

Chapter 6: Final conclusions and future work

Tool Condition Monitoring (TCM) is one of the most extensively studied fields of manufacturing. The need for a perfect TCM system has resulted in the development of a variety of technologies used in tool condition monitoring, and these can broadly be classified into direct and indirect systems. The advanced TCM systems and its applications, however, have failed to transition from lab setup to machine shop setup. The failure can be attributed to numerous reasons; one of the main reasons is the lack of objective for TCM. TCM, in itself, adds no value to the manufacturing process. TCM, on the other hand, can be an ally if used with a proper objective. Tool condition affects different facets of machining like quality, tool life, production time, production cost, among others; therefore, the objective of TCM can also be different. TCM system developed with one of the objectives mentioned previously gives the machine operators the vision to see the future.

The presented work is an effort to provide objective and direction to TCM and has four parts. In the first part, the barriers to the transition of TCM from laboratory setups to machine shop setups are investigated; in the second part, a framework that uses TCM for machining quality management is developed; in the third section, a fuzzy controller is developed. The controller uses TCM as feedback to make the right decision. In the final section, a three-dimensional description is developed to carry out TCM for forming tools. The developed frameworks and systems set an example for how TCM can be used with a specific objective.

6.1 Contribution of the study

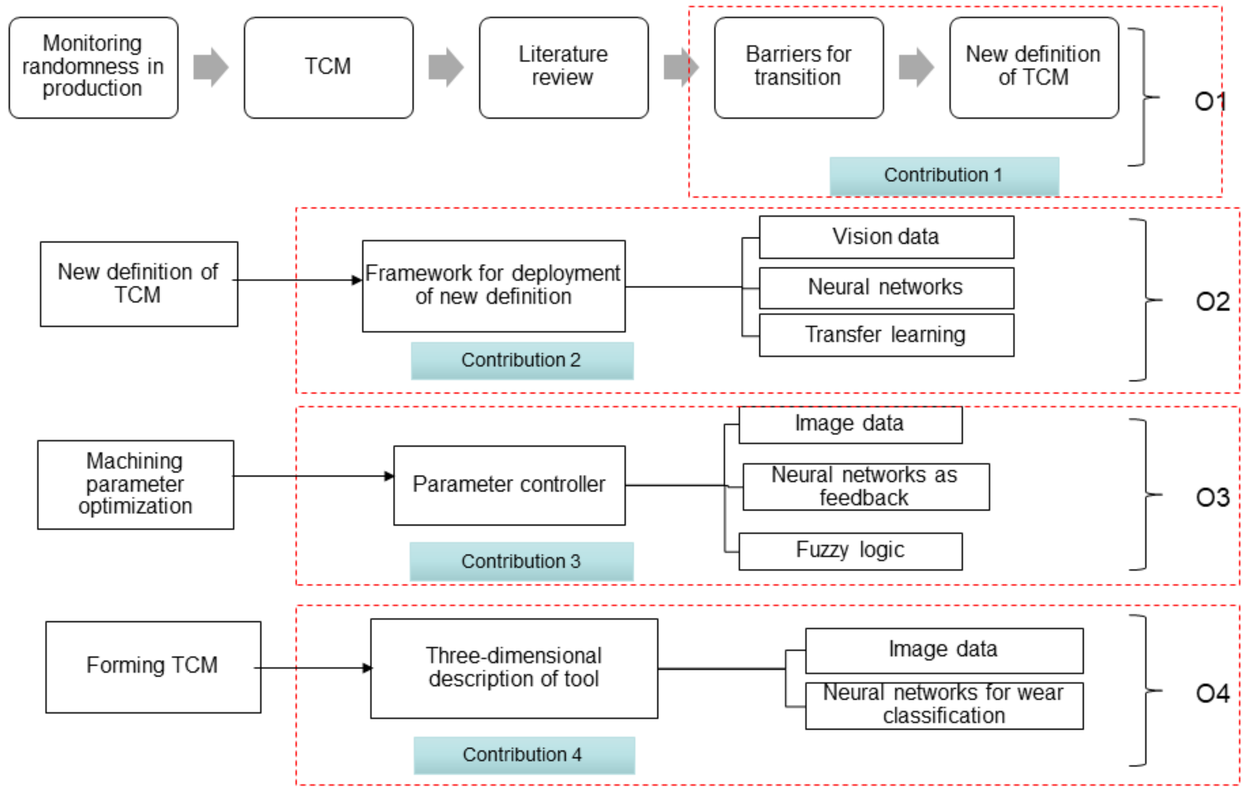


Fig. 6.1 Research objectives and contributions

Earlier in Section 1.6, the objectives of the studies were defined. Fig. 6.1, gives an overview of these objectives and the contributions; each is summarised in the following points:

1. The first objective was to understand the barriers to the translation of existing TCM technologies from laboratory setup to an industrial setup. As part of these objectives, an extensive review of the existing technologies involving 42 studies, as summarised in Annexure a is done. The review resulted in redefining TCM; the new definition and the barriers it addresses are summarised in Section 2.4.
2. The new definition that overcame the barriers to the transition from laboratory setup to industry setup needs a new framework that implements the new definition; this is the second objective of the study. The developed framework uses concepts of convolution

neural network and transfers learning. This framework classifies the cutting tools into GO category (i.e. conforming parts) and NO GO (i.e. non-conforming parts) with 85 percent accuracy using just 37 images for training and 12 training iterations.

3. Machining parameters are critical manufacturing variables as they affect various facets such as surface finish, load on machine, power consumption, and tool life. Usually, these parameters are optimized by trial and error using expert knowledge. The need for a generalized system for machining parameter optimization that can work with different materials, tool geometries, and grades was evident from the literature. In response, a fuzzy controller using deep learning TCM framework as feedback is developed. The experiments showed that using the controller can improve tool life by 100 percent.
4. A TCM framework for forming tools such as grooving and threading is developed. The framework makes a case for using three-dimensional descriptions of the forming tools to determine the tools' useability. Since these tools take the heavy depth of cuts, which engages multiple surfaces of the tools.

6.2 Limitation of the study

The frameworks that are developed as part of the research objectives are carefully examined with the existing literature. There are, however, particular limitations and reasonable assumptions that are used in the evolution of the proposed method. These limitations and reasonable assumptions are as follows:

- Data limitation is one of the overarching limitations of all the systems developed. For example, to train the qualitative model, 79 images of damaged inserts, 121 images of deformed inserts, and 128 images of abrasive wear are used. While care was taken to validate the systems using test data sets not used in training, more image data can improve accuracy, which currently is 85 percent, and the systems' reliability. Generating the data, however, is a costly affair. Cutting tools have to be used to their full life using abnormal cutting conditions, which requires new cutting inserts and CNC machine time.

- For a framework that correlates TCM with machining quality, the study reasonably assumes the machining environment like fixtures, condition of the CNC machine, and machining parameters are stable and are not changing. This assumption is justified as the mass production lines are set up, these environmental factors are optimized, and after the optimization, they are rarely changed.
- For a framework that uses TCM as feedback for machining parameter optimization, the study is limited by the capabilities of the mini late machine used in the evaluation. The machine only allowed cutting speed control. The feed was automatic by means of leadscrew engagement. The feedback of the type of wear to the fuzzy controller, and the implementation of the cutting speed change suggested by the fuzzy controller are done manually.
- The images for the qualitative framework and the fuzzy controller are captured using standard room lighting using an external station. The station has about one meter between the tool holder and the camera.
- The TCM framework developed and discribed in chapter Chapter 5: for forming tools is validated using synthetic data. The three-dimensional description of the tools is recreated in synthetic data, and it is assumed the synthetic data closely resembles the real data.
- The Forming TCM framework is developed for a single point forming tool and can’t be used for multipoint threading or grooving tools.

6.3 Future work

Each of the frameworks developed has certain advancements that need to be achieved before these frameworks are ready to be deployed in a real machine shop environment. These advancements are discussed in the following sections.

6.3.1 Quality framework advancements

The image acquisition for the training and validation of the framework is done offline station. For the framework to be integrated into the machine, the camera needs to be integrated into the CNC machine. The camera is working in between machining cycles to determine the useability of the tools. But there are challenges related to lubrication and metal chips that might interfere with the image. There is a need to develop a protective cover before the integration.

The internet of things (IOT) implementation of quality management, where the person monitoring remotely can be notified to change the cutting tool, will also go a long way in the realization of lights out machining.

6.3.2 Machining parameter optimization advancements

The machining parameter optimization framework only considers cutting speed; there is a need to integrate feed and depth of cut in the controller before it can be characterized as a complete parameter optimizer. There is also a need to automate the interaction between the TCM feedback and the fuzzy controller. Finally, the output of the fuzzy controller also has to be integrated with the CNC machine controller, which can manipulate the cutting speed, feed, and depth of cut, this will allow the CNC machine to manage machining parameters autonomously.

The fuzzy controller responses are modeled around the remedy actions suggested by the cutting tool manufacturer's suggestions but thses remedy actions only give the direction of change in terms of increase or decrease in cutting paramenter; there is a need to further develop data about the impact of the magnitude of changes in the machining parameters. More data about the impacts of changes will further improve the fuzzy controller actions and improve the tool life.

6.3.3 Forming tool condition monitoring

The forming TCM framework is validated using synthetic data taken from virtual models, mainly because developing a three-dimensional description requires a special setup. In future work, a system that is capable of generating a three-dimensional description as shown in Fig. 6.2 must be developed before the artificial intelligent framework can be deployed.

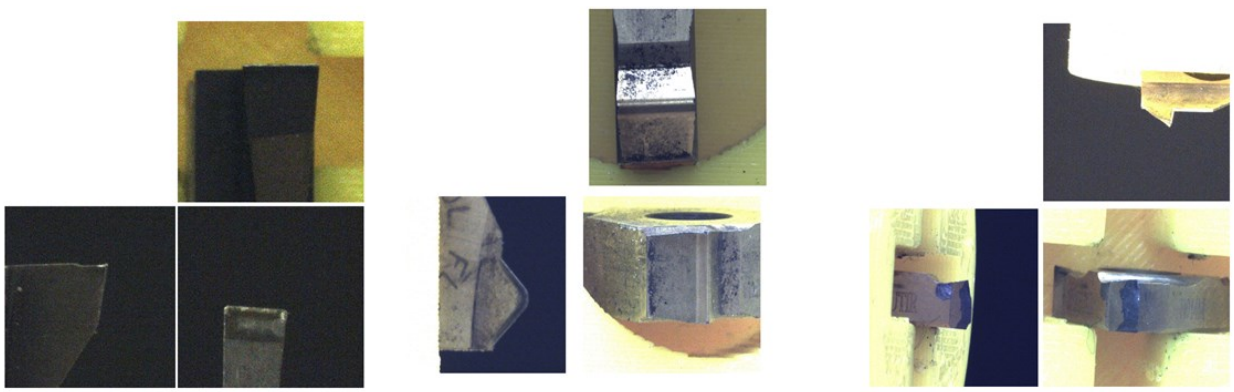


Fig. 6.2 Examples of three dimensional discriptions for tool condition monitoring

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Annexures a

SLN0	Reference	Method	Technology	AI Algorithm	System input	System output	Disadvantages	Generalization	Need for TCM and notes
1	Teti.R et.al 2010[59]							Doesn't address	1) Many process variables are affected by the condition of the tool.
2	Kilundu.B et al. 2010[35]	Indirect	Vibration sensor	Singular spectrum analysis	Vibration to system	Tool wear	Vibration signal processing is prone to noise	Difficult to generalize the system for different tool and operations	1) Tool condition affects dimensional tolerance and other quality aspects of machining. 2) ANN working explained can be referred
3	Wang.G et al. 2012[41]	Indirect	Force sensor	Distributed Gaussian ARTMAP	Force signals	Tool condition	Complex system for deployment	Doesn't address	1)Contribution of AI to tool condition monitoring has improved.
4	Wang.G.F et al. 2014[43]	Indirect	Vibration sensor	Support vector machine	Vibration sensor	Tool condition	Vibration related to four types of wear have been collected this limits the useability of the system	Doesn't address	1)Tool condition has effects on different aspects of machining.
5	Painuli.S et.al 2013[120]	Indirect	Vibration sensor	K-star algorithm	Vibration signals	Tool condition / surface finish	The complex system as it requires vibration signal receiver closer to metal cutting	doesn't address	1) Importance of tool condition monitoring for autonomous manufacturing systems. 2) Direct methods more accurate.
6	Balsamo.V 2015[46]	Indirect	Acoustic Emission		Force and acoustic signals	Catastrophic tool failure	The complex system that uses force and acoustic signals and there is a delay in failure detection	doesn't address	1) Tool condition monitoring can aid in full utilization of tool life. 2) Tool condition monitoring defined by three steps, sensing signals, signal processing, classification.

									3) Catastrophic tool failure during machining is bad.
7	Dongre.P 2013[53]	Indirect	Acoustic Emission	Acoustic signature Analysis	Acoustic Emissions	Tool condition and failure	Requires sensing of signals close to cutting operation	Considered generalization for different cutting operations like milling, turning, drilling	1) Early tool changing is a problem. 2) Tool condition monitoring is necessary for autonomous manufacturing. 3) Tool condition monitoring is not just monitoring tool wear.
8	Aghazadeh. F 2018[14]	Indirect	Electrical resistance	Support vector machine, Bayesian rigid regression, Nearest neighbor regression, Decision tree	Electrical signals from spindle	Tool wear estimation	Complex system for analysis	Doesn't address	1) Tool defects can be considered as one of the most common and costly faults of machining processes. 2) Tool condition monitoring improves accuracy, reduces the production cost and increases productivity. 3) Direct methods more accurate. 4) Direct methods more expensive and not suitable for online applications.
9	Roth.J 2010[121]								1) There is a need for a single unified approach, and a unified approach will enable rapid expansion of tool condition monitoring into other processes and tighter integration. 2) Tool condition monitoring extracting features that help in determining the health of the equipment. 3) Different sensors are used to obtain those features.

									4) Historical behavior or human expertise can be used to define the undesired features. 5) Quantitative health assessment is common. 6) The online systems are done in a harsh and extreme condition which may affect the performance.
10	Torabi.A.J 2016[40]	Indirect	Force sensor	Clustering methods	Force and vibration	Surface quality/ tool wear	Requires sensing of signals close to cutting operation	Mentions generalization	1) Can be used to explain the force-sensing concept.
11	Kaya.B 2012[32]	Indirect	Force sensor	Support vector machine, Genetic algorithm	Force and acoustic signals	Tool condition		Doesn't address	1) The quality of the machine has a direct correlation with the tool condition. 2) sharp tools for finishing. 3) Operator judgment may be flawed in high precision machining. 4) machine operator is responsible for tool condition assessment. 5) Tool condition monitoring is a barrier for unmanned machining. 6) High-class tool condition monitoring is essential for high volume manufacturing like in automotive. 7) Three-component of TCM sensing, feature

									extraction, and decision making.
12	Shi.C 2018[42]	Indirect	Vibration sensor	Deep learning	Acccelerometer	Tool life quantification	Quantification of tool wear is not required for tool condition monitoring	Doesn't address	1) Deep learning has been used in manufacturing classification tasks to forecast part quality. 2) The microwear of tools affects the quality of the products manufactured. 3) Classified the algorithms used into two a) Man-made expert knowledge-based feature extraction b) Shallow layer model development and study like NN, HMM, SVM. 4) Models developed are only used in labs and are prone to noise and uncertainty when applied to real life. 5) There is a need for autonomous feature extraction. 6) NN can learn features

13	Geramifard. O 2012[48]	Indirect	vibration sensor	Markov models	Accelerometer, Acoustic sensor, Dynamometer	Tool health	Complex setup for deployment	Addresses generalization	1) Specifies the need for flexible decision-making systems for different quality requirements
14	Massol.O 2010[45]	Indirect	Acoustic Emission	Neuro-Fuzzy model	Accelerometer, Acoustic sensor, Dynamometer	Tool health	Complex setup requires sensors closer to cutting operation	Talks about insufficient generalization capabilities of systems	1)Talks about insufficient generalization capabilities of systems. 2) Different tools perform differently.
15	Jemielniak. K 2012[47]	Indirect	Acoustic Emission	Signal processing	Accelerometer, Acoustic sensor, Dynamometer	Tool wear estimation	Requires complex features extraction	Doesn't address	
16	Liu.T 2015[39]	Indirect	Force sensor	Neural networks	Dynamometer	Tool state / Tool wear value	Complex setup requires sensors closer to cutting operation	Doesn't address	1) TCM has the potential of eliminating catastrophic failure and maintain quality.
17	Shankar.S 2018[122]	Indirect	Force sensor	Neural networks	Dynamometer, Microphone	Progress of tool wear	Predefined level of wear is defined, and this is a problem for generalization	Doesn't address	1) Tool condition monitoring can be divided into two parts direct and indirect. 2) Usually tool maker microscope is used to quantify the tool wear indirect methods.
18	Wang.G 2014[54]	Indirect	Force sensor	Support vector machine, Hidden Markov model, radius basis function	Dynamometer	Tool wear state	Requires sensing of signals close to cutting operation	Mentions generalization	1) Tool condition monitoring helps in improving machining efficiency and guarantee workpiece quality. 2) TCM needs a robust classifier of good and bad tools using relationships between sensor signals and tool condition.

19	Siddhpura.A 2012[13]							Doesn't address	1) Flank wear is unavoidable wear pattern. 2) TCM is a) Signal acquisition b) Feature extraction c) Decision making. 3) Direct methods include optical, radioactive, electrical. 4) Good source for direct methods review. 5) Optical method most popular indirect methods. 6) Force most popular indirect methods
20	Ali.Y.H 2014[123]	Indirect	Acoustic Emission					Doesn't address	1) A good source for AI technologies. 2) AI allows for the integration of new data
21	Zhang.K 2015[124]	Indirect	Acoustic Emission	Support vector machine	Microphone	Tool condition	Requires sensors to be mounted near to cutting	Doesn't address	1) Proposes data fusing or sensor fusion technique.
22	Dutta.S 2013[38]	Direct	Computer vision	Image processing	Camera and lighting	Surface quality	Tool condition monitoring not directly addressed	Doesn't address	1) Excessive wear and breakage is one of the severe causes of downtime. 2) Indirect tool monitoring is studying different behavior of machine tools. 3) There is research on making direct methods noninvasive. 4) The direct purposes require processing the images
23	Ghani.J.A 2011[5]	Indirect	Force sensor	Data analysis	Strain sensor	Tool wear	1) Quantification of tool wear is not required for tool	Doesn't address	1) 20% of downtime attributed to machine tools and between 3 to 12 % production cost.

							condition monitoring 2) Used images of tool to generate y labels for the Study using a microscope		2) TCM studied since the 1980s. 3) Direct methods have the advantage of capturing the geometrical changes in tools.
24	Loizou.J 2015[33]	Direct	Computer vision	Image processing	Microscope	Tool wear	Requires image processing and concentrates on quantification	Doesn't address	1) Tool wear is an unavoidable irreversible process that can lead to nonconforming parts, poor surface finish, a catastrophic failure like tool breakage. 2) Usually tool condition monitoring is based on expert opinion by classifying wear into different levels or stages.
25	Dutta.S 2013[51]	Direct	Computer vision	CCD camera				Doesn't address	1) Improvement in vision system has made direct methods more popular. 2) Tool condition monitoring is inevitable for higher production rate and lower production cost. 3) Different types of wear like flank wear, crater wear, and abrasive wear are discussed. 4) Digital image processing technique is useful for fast detection of crater wear, chipping and fracture difficult in other indirect techniques.
26	Chethan.Y.D 2014[34]	Direct	Computer vision	image processing	camera	Establish a relation between cutting	Sophisticated image processing and feature	Doesn't address	1) Tool wear highly correlated with production time and cost.

						parameters and tool wear	extraction required and only limited to drilling application		2) One of the primary objectives of tool condition monitoring is establishing tool change policy.
27	Chethan.Y.D 2015[125]	Direct	Computer vision	Image processing	camera	Tool status and time for replacement	Requires prepocessing and segmentation operation	Doesn't address	1) Tool condition monitoring facilitates in full utilization of tool by reducing unnecessary tool change. 2) Different direct monitoring techniques Visual inspection, laser beam, electrical resistance. 3) Indirect methods tool condition is estimated using signal features
28	Mandal.S 2014[126]								1) There is a need or tool condition monitoring in batch production. 2) Metal cutting results in tool wear which can be seen consequences like machining force, deformation, chatter and vibration. 3) The datasheets for machining parameters don't sometimes work as they don't give all combinations of optimal parameters.
29	Abdul-Ameer.H.K 2011[127]	Direct	Computer vision	Image processing	camera	Surface quality	Limited to surface finish	Doesn't address	1) The Study doesn't concentrate on the tool but surface finish of the machined component this limits the Study to just surface finish.
30	Sharma.K 2017[128]	Direct	computer vision	image processing	camera	Tool state normal or worn	Requires feature extraction and	Doesn't address	1) Tool condition necessary for evaluation of tool life and timely replacement.

							concentrates on measuring the wear		2) Defines flank wear. 3) Indirect monitoring can be costly. 4) Different image processing techniques are stated.
31	Prasad.B.S 2011[129]	Indirect	Vibration sensor	Real-time monitoring no prediction using AI	Laser doppler vibrometer, CCD camera	Tool condition/surface finish	Complex system for deployment and mainly concentrates surface finish	Doesn't address	1) Important to detect and replace worn tool in time. 2) None of the developed methods have been able to universally apply the tool condition monitoring due to the complexity of the machining process.
32	Elgargni 2014[130]	Direct	Vibration sensor	Principle component analysis, Discrete wavelet transform, neural networks	Infrared sensor, vision systems	Tool health	Uses complex infrared image processing and AI models	Doesn't address	1) Noncontact technology is essential for tool condition monitoring. 2) Indirect signals are case dependent. 3) Sensors used in one study not successful in other studies. 4) Location of sensors is a problem in indirect methods.
33	Hou.Q 2019[12]	Direct	Computer vision	Image processing	Camera and lighting	Tool wear estimation	Uses complex lighting systems	Doesn't address	1) Tool condition monitoring is essential for high volume manufacturing. 2) Tool condition monitoring can save up to 30 % of processing cost. 3) Indirect methods are not accurate and are easily affected by the industrial environment.
34	Setiawan. 2018[31]	Indirect	Temperature	Data analysis	Temperature sensor, Accelerometer, Electrical power	Tool wear	Using a complex system with three sensors and requires	Doesn't address	1) Industry 4.0 needs assets to be remotely monitored.

					consumption sensor		human intervention to determine the tool condition		
35	Zaretalab.A 2018[131]	Direct		Policy method			Develops a policy that is similar to what is used in the industry and based on any autonomous systems		
36	Klancnil.S 2015[132]	Direct	Computer vision	Image processing, K nearest neighbor and neural network	CCD camera	Tool condition	Requires feature extraction and requires further development for turning	Doesn't address	
37	Wu.J 2019[133]		Data fusion	Deep long short term memory neural network		Remaining useful life prediction	The model is for engine useful life prediction		1) Remaining useful tool life prediction helps in preventing significant economic losses and catastrophic consequences. 2) Classifies tool condition monitoring into a) model-based methods b) data-driven methods c) hybrid methods. 3) ADAM algorithm is used this can be used for reference.

38	Sun.H 2019[37]	Indirect	Data fusion	Convolution neural network	Dynamometer, Accelerometer, Acoustic emission sensor	Forecast flank wear values	Complex setup requires sensors closer to cutting operation	Doesn't address	1) There is a need for a proactive approach to tool condition monitoring. 2) Study show that only 50 to 80% of tool life is used. 3) Tool wear estimation is challenging because it is dynamic, time-varying nonlinear and stochastic process. 4) Every cutting tool has a unique wear curve. 5) Data-driven methods are more feasible because of unavailability of reliable physical-based model.
39	Wu.J 2017[134]	Indirect	Data fusion	Neural networks, Fuzzy logic	Dynamometer, Accelerometer, Acoustic emission sensor, Motor current sensor	Flank wear	Complex setup requires sensors closer to cutting operation	Doesn't address	1) The tool wear is nonlinear and stochastic which makes it challenging to develop the relation between extracted features and tool wear. 2) Gives classification of a) Model-based methods b) Data-driven methods. 3) model-based methods quantitatively characterize failure behavior. 4) Data-driven methods use data acquired from sensors to do tool condition monitoring. 5) Data-driven methods more equipped to handle the complexity of failure mechanisms
40	Kurek.J [135]	Direct	Computer vision	Convolution neural network, transfer learning,	camera	Tool condition	Only limited to holes challenging to apply to other shapes	Doesn't address	1) Transfer learning reduces the data requirement.

				Support vector machine					
41	Wu.X 2019[61]	Direct	Computer vision	Convolution neural network	CCD camera	Tool wear estimation	Concentrates on quantification of tool wear but tool wear is subjective to different quality requirements	Doesn't address	1) Traditional visual methods require expert experience to obtain wear information. 2) Signals in indirect methods are contaminated by the noise, which compromises the accuracy of models in industrial setups. 3) Direct methods are more accurate. 4) Neural networks allow to exclude data preprocessing from the system.
42	Sun.W.H 2018[16]	Direct	Computer vision	Image processing	CCD camera	Tool condition	Requires feature extraction	Doesn't address	1) The system identifies the different types of wear patterns. 2) To get the best machining quality, the manufacturers must be aware of tool behavior and determine when the tool needs to be changed. 3) Flank wear gradually occurs due to erosion of a portion of the insert in contact with workpiece which is unavoidable. 4) External environment affects indirect methods.

Annexures b

Input to the fuzzy controller				Output of the fuzzy controller					
Cut	Diameter	rpm	GUI output	V_c	New diameter	Amount of wear	New V_c	New rpm	Length
				TOOL 1					
1	28.11	260	Normal	23	27.93	0	23	262	78
2	27.93	262	Normal	23	27.55	0	23	266	156
3	27.55	266	Normal	23	27.21	0	23	269	234
4	27.21	269	BUE	23	26.73	0.44	32	383	312
				TOOL 2					
1	26.73	383	Normal	32	26.37	0	32	388	78
2	26.37	388	Normal	32	26	0	32	394	156
3	26	394	Normal	32	25.82	0	32	397	234
4	25.82	397	Normal	32	25.23	0	32	406	312
5	25.23	406	Normal	32	25	0	32	410	390
6	25	410	Normal	32	24.6	0	32	417	468
7	24.6	417	Normal	32	24.32	0	32	422	546
8	24.32	422	Normal	32	23.98	0	32	428	624
				TOOL 3					
1	24.6	500	Normal	39	24.46	0	39	503	78
2	24.46	503	Normal	39	23.8	0	39	517	156
3	23.8	517	Deformation	39	28.53	0.33	31	345	234
				TOOL 4					
1	28.53	345	Normal	31	28.14	0	31	350	78
2	28.14	350	Normal	31	27.75	0	31	355	156
3	27.75	355	Normal	31	27.41	0	31	359	234
4	27.41	359	Normal	31	26.92	0	31	366	312
5	26.92	366	Normal	31	26.53	0	31	371	390
6	26.53	371	Normal	31	26.24	0	31	375	468
7	26.24	375	Normal	31	25.8	0	31	381	546
8	25.8	381	Normal	31	25.45	0	31	386	624