

Alireza Falah

THESIS

EÖTVÖS LORÁND UNIVERSITY  
FACULTY OF INFORMATICS  
SAVARIA INSTITUTE OF TECHNOLOGY



MSc THESIS

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FACULTY OF INFORMATICS  
SAVARIA INSTITUTE OF TECHNOLOGY

ALIREZA FALAH

MSc THESIS

*Tool Monitoring in CNC machines based on Image Processing*

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Szombathely, 2024.

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**Topic of the Thesis:**

*(Upon consulting with your supervisor, give a 150-300-word-long synopsis of your planned thesis. )*

This thesis delves deeply into the development and implementation of a camera-based monitoring system for CNC (Computer Numerical Control) machines, with a primary focus on the transformative role of image processing in tool and workpiece monitoring. By capturing and analyzing intricate details of the machining process, this study pushes the boundaries of traditional methods which have been constrained by limitations in real-time data acquisition and analysis. Using state-of-the-art machine vision techniques, the research offers a granular view of the tooling process, enabling the detection of minute changes in tool integrity and orientation. Additionally, advanced machine learning algorithms are harnessed to intelligently interpret this data, bringing forth a comprehensive evaluation of the tool's condition and workpiece's placement. The outcome is a significant departure from traditional tool wear monitoring methods, presenting a system that is not only more efficient but also provides insights in real-time. This thesis underscores the potential of integrating machine vision with machine learning to revolutionize CNC machine monitoring, and by extension, promises enhancements in manufacturing productivity, quality, and safety.

Tasks and sub-tasks: (listed in 4-6 points)

1. Literature review.
2. System Design and Setup
  - 2.1 Detail the hardware components, including camera selection and placement.
  - 2.2 Design the method for capturing tool rotations, determining frame extraction rate, and setting the optimal tool rotation speed.
3. Image processing and segmentation
4. Machine learning model training
5. Results and evaluation
6. Summary of Results gained

Budapest, 2023. 10. 21.

## STATEMENT

### *A statement about independent, original work*

I, the undersigned, Alireza Falah (VJ92LE), a student at Eötvös Loránd University, hereby declare and certify with my own signature that I have prepared this thesis without any unauthorized assistance, I have prepared it myself and used only those sources that I have provided in my dissertation. Any part that I have taken from another source, either verbatim or in the same sense, but rephrased, has been clearly marked by indicating the source in accordance with the current regulations. I am the original author of this thesis and this independent intellectual work complies with the “Organizational and Operational Regulations of Eötvös Loránd University, II. Volume, Student Requirements System, With Amendments. 2017. September 1<sup>st</sup>. Regulation: 74/A–74/C. §”.

Szombathely, 2024. April

*signature of the student*

A handwritten signature in black ink, appearing to read 'Alireza Falah', is centered below the text 'signature of the student'.

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# FOREWORD

*If you're reading this, you're either my advisor, my examiner, or someone who's really into CNC machines. Either way, I appreciate your time.*

*I must admit, there were times during this process when I felt like the tools I was studying: worn out and on the verge of breaking. But, unlike a CNC tool, I couldn't just be replaced with a new, sharper version of myself. Instead, I kept grinding away (pun intended) until I reached the finish line.*

*To those who find themselves in the middle of their own academic machining process, remember: even the dullest tool can finish the job with enough persistence and the occasional well-timed break (and maybe a drink or two).*

*So here it is, my contribution to the world of tool condition monitoring. May it serve as a testament to the fact that even in the most technical of fields, there's room for a little humor and a lot of perseverance.*

\* \* \*

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Szombathely, 2024 May

*Alireza Falah*

## NOTATIONS

The table below provides the notations used in this thesis, along with their full names.

| Notation | Full Name                                      |
|----------|------------------------------------------------|
| AI       | Artificial Intelligence                        |
| ANN      | Artificial Neural Network                      |
| BLMD     | Bidimensional Local Mean Decomposition         |
| CAX      | Computer-Aided Technologies                    |
| CCD      | Charge-Coupled Device                          |
| CNC      | Computer Numerical Control                     |
| CNN      | Convolutional Neural Network                   |
| CPPS     | Cyber-Physical Production Systems              |
| DL       | Deep Learning                                  |
| DMLP     | Deep Multi-Layer Perception                    |
| FCM      | Fuzzy C-Means                                  |
| I4.0     | Industry 4.0                                   |
| IoT      | Internet of Things                             |
| ISO      | International Organization for Standardization |
| ML       | Machine Learning                               |
| OWL      | Web Ontology Language                          |
| PLC      | Programmable Logic Controller                  |
| QFCM     | Quick Fuzzy C-Means                            |
| ROI      | Region of Interest                             |
| RSM      | Response Surface Methodology                   |
| SCM      | Statistical Color Model                        |
| SHFCM    | Statistical Histogram-Based Fuzzy C-Means      |
| SIFT     | Scale-Invariant Feature Transform              |
| SURF     | Speeded-Up Robust Features                     |
| TCM      | Tool Condition Monitoring                      |
| YOLOv8   | You Only Look Once (Version 8)                 |

# 1. INTRODUCTION

## 1.1. Aims

In the highly competitive manufacturing sector, maintaining an ideal Computer Numerical Control (CNC) environment, including optimal tool and workpiece conditions, is essential for enhancing productivity, minimizing costs, and guaranteeing product quality. Traditional tool condition monitoring methods often face challenges in accuracy, adaptability, and real-time applicability, which can lead to increased downtime, higher operational costs, and compromised product quality.

This thesis presents the development and implementation of an innovative camera-based monitoring system for CNC machines, aimed at addressing these challenges. The objective of this thesis is to offer a comprehensive understanding of the proposed system, including its design, implementation, and performance evaluation. The specific aims are summarized as following:

1. Identify the Limitations of Traditional Monitoring Methods: Examine the current methods used in tool condition monitoring within CNC environments, and identify the specific limitations and challenges associated with these traditional methods, such as accuracy issues, high costs, and inability to provide real-time feedback.
2. Develop a Camera-Based Monitoring System: Design a novel system using consumer-grade cameras for real-time monitoring of CNC tools. Implement image processing techniques to detect tool breakage and fracture and ensure the system can provide accurate and timely feedback on tool conditions to minimize downtime.
3. Evaluate the Performance of the Proposed System: Conduct extensive testing and validation of the camera-based monitoring system in real-world CNC machining scenarios, and analyzing the potential benefits, such as reduced downtime, lower operational costs. Suggest directions for future research to enhance the capabilities and performance of tool condition monitoring in CNC machines.

By achieving these aims, this thesis seeks to contribute to the field of manufacturing by providing an innovative solution to the challenges of tool condition monitoring in CNC environments. The proposed camera-based system aims to enhance produc-

tivity, reduce costs, and ensure high-quality manufacturing processes, ultimately supporting the advancement of Industry 4.0 initiatives.

## **1.2. Overview**

In manufacturing industries, conventional machining operations, such as turning, milling, drilling, and grinding, are classified as the most common activities in production environments. With the rapid development of computer applications and technology, conventional machining has been gradually transformed into modern machining operations with efficient support for large-scale manufacturing. Although many of these advancements in machining have been implemented based on the programming language known as G-code (ISO 6936), it is a low-level programming language with a limited amount of information and is unable to provide data feedback [1].

As a result, CNC machines have limited capabilities in terms of their movement. They follow the programmed input even if unsuitable machining parameters are assigned. Furthermore, in the absence of a monitoring system, these scenarios may result in machine tool downtime. Machine downtime is defined as a certain duration of time during which no machining operation can be done on the workpiece [2] and can be divided into two—unavoidable and avoidable [1]. The former occurs due to machine maintenance or any replacement of the machine components, while the latter is due to disturbances during machining processes, which include overloading of spindle torque, excessive cutting force, chatter, tool wear, and other constraints [3]. Machine downtime due to tool breakage has been estimated to average 6.8% [4] but can be up to 20% [5]. Traditional methods of tool monitoring face significant challenges, including issues with accuracy, adaptability, and real-time applicability. Additionally, the expenses related to the necessary equipment further complicate the implementation of effective monitoring systems.

Given these challenges, the development of innovative and efficient monitoring techniques has become a critical area of interest and continues to be an active field of research. This thesis aims to address these issues by proposing an innovative camera-based monitoring system for CNC machines. The proposed system seeks to enhance the accuracy and reliability of tool condition monitoring, reduce machine downtime, and improve overall manufacturing efficiency.

### **1.2.1. Methods**

This thesis explores two distinct approaches for tool condition monitoring in CNC machines. The initial approach involved using a deep learning model, YOLOv8 (You Only Look Once), for tool detection and segmentation. After encountering several challenges, a more traditional image processing-based method was adopted. Below is a brief introduction to each method.

#### **1.2.1.1. Initial Approach: Using YOLOv8 for Tool Detection and Segmentation**

The first method attempted was to leverage the YOLOv8 deep learning algorithm, known for its efficiency and accuracy in object detection tasks. This approach aimed to:

1. Dataset Collection and Annotation: Gather a comprehensive dataset of images containing various CNC tools in both intact and broken states. Each image was manually annotated to mark the tool boundaries, creating a labeled dataset for training the YOLOv8 model.
2. Training the YOLOv8 Model: Train the YOLOv8 model on the annotated dataset to detect and segment the tools from the background.
3. Edge Detection and Background Adjustment: Implement refinements such as Canny edge detection and the use of a corrugated fiberboard background to enhance tool visibility and improve segmentation accuracy.

Despite these efforts, this approach faced significant challenges:

- Infinite Breakage Patterns: The numerous possible ways a tool can break made it difficult for the model to generalize from a limited dataset.
- Complex Backgrounds: Detecting tool edges against varying backgrounds proved problematic, even with enhancements.
- Data Collection Constraints: Extensive data requirements and the high cost of acquiring multiple tool samples limited the feasibility of this method.

#### **1.2.1.2. Current Method: Image Processing-Based Approach**

Due to the challenges encountered with the YOLOv8 approach, a more traditional image processing-based method was adopted. This method involves several steps:

1. Image Acquisition and Setup: Utilize a consumer-grade camera, such as an iPhone 12 Pro, to capture high-resolution images and videos of CNC tools at the changing position.
2. Region of Interest (ROI) Identification: Define the ROI based on the fixed position of the spindle face, ensuring consistent location across different operations.

3. Background Subtraction: Capture a reference frame without the tool to use as a baseline for isolating the tool in subsequent images.
4. Grayscale and Binary Thresholding: Convert the ROI to grayscale and apply binary thresholding to enhance tool visibility.
5. Morphological Closing and Contour Analysis: Refine the image by closing small gaps within the tool's silhouette and identifying the largest contour representing the tool.

This method proved to be more reliable and feasible for real-world applications due to its:

- Deterministic Results: Provides predictable and consistent results without the need for extensive model training.
- Resource Efficiency: Leverages readily available tools and techniques without requiring specialized equipment or large datasets.

The comparison of these methods and the transition from the YOLOv8 approach to the image processing-based approach provides a comprehensive understanding of the proposed system, its challenges, and its advantages in the context of CNC tool condition monitoring.

### **1.3. Assumptions**

In conducting this research on tool condition monitoring in CNC machines, some assumptions were made to define the scope and ensure the feasibility of the study:

- Consistency of CNC Machine Operation: It is assumed that the CNC machines operate under consistent conditions during the monitoring process. This includes stable environmental conditions (temperature, humidity) and regular machine maintenance to minimize external variables affecting the results.
- Tool Visibility: It is assumed that the tools are adequately visible during the image capture process. The camera placement and lighting conditions are assumed to be optimal for capturing clear images of the tools without significant obstructions or shadows.
- Fixed Camera Position: The camera used for capturing images and videos is assumed to remain in a fixed position relative to the CNC machine's changing position. This ensures consistency in the region of interest (ROI) and simplifies the image processing tasks.

By outlining these assumptions, the research scope is clearly defined, and the basis for the methodology is established.

## 2. LITERATURE REVIEW

### 2.1. Introduction to Industry 4.0 and Smart Manufacturing

Industry 4.0, often termed I4.0, symbolizes the fourth revolutionary wave in manufacturing, underpinned by rapid strides in digital technology, automation, and data analytics. It is distinctly characterized by the integration of modern technologies and concepts, including the Internet of Things (IoT), cloud computing, mobile internet, and predominantly, Artificial Intelligence (AI) [6]. These advancements have collectively transformed traditional manufacturing processes into highly interconnected and intelligent systems.

This transformative shift has led to an exponential surge in data, particularly from manufacturing shop floors, bringing 'Big Data' to the forefront of manufacturing challenges [7]. To harness this data effectively, advanced computational techniques such as Machine Learning (ML) and Deep Learning (DL) have been employed. These methods have reshaped traditional manufacturing paradigms, from automating feature selection to facilitating optimal data fusion for varied analytic applications [6].

The modules of data-driven smart manufacturing, as outlined by Tao et al. [8], further elucidate the structure and functionality of this approach. These modules include:

- *Manufacturing Module*: Transforms raw material into the finished product.
- *Data Driver Module*: Implements the smart manufacturing approach throughout the data lifecycle, supporting real-time monitoring and problem processing.
- *Real-Time Monitor Module*: Provides a critical step that enforces quality improvement through real-time insights, allowing for condition monitoring and preventive maintenance.
- *Problem Processing Module*: Uses intelligent monitoring to enhance decision-making in a system.

As these intelligent systems become more prevalent, the need for precise and efficient monitoring techniques becomes increasingly critical. Among the various technologies enabling this precision, image processing has emerged as a key component [9]. Image processing techniques allow for automated inspection, defect detection, and process control, significantly enhancing the capabilities of smart manufacturing systems [10]. The following section delves into the specific role of image processing in industrial applications, highlighting recent advances and their impact on manufacturing processes.

## **2.2. Image Processing Techniques in Industrial Applications**

Recent advances in sensor quality and processing power have significantly enhanced the capability to design complex image processing and pattern recognition tasks, particularly in industrial applications [10]. Image processing has become an integral component of advanced manufacturing systems, enabling various applications such as automated visual inspection, process control, and robotic guidance [10].

In modern industrial settings, monitoring various parameters such as temperature, voltage, and the environment is crucial. Traditional methods relying on manual power pose significant risks, particularly in hazardous conditions [11]. Consequently, automation through advanced technologies like image processing, machine learning, and IoT has become essential. These technologies enable continuous and accurate monitoring, reducing dependency on manual intervention and enhancing safety and efficiency in industrial operations [11].

### ***2.2.1. Intro to image processing in industry***

A typical industrial vision system typically involves several key components: image acquisition, processing, segmentation, feature extraction, and decision-making [10]. The process begins with properly illuminated and arranged scenes to facilitate good image acquisition using fixed-position cameras. The acquired images undergo processing to remove noise and non-uniform lighting, followed by segmentation to partition the image into regions of interest. Feature extraction then reduces the information to describe the data set accurately, and decision-making involves matching these features against known models to ensure quality standards are met [10].

Image processing algorithms play a pivotal role in industrial monitoring by enabling automated inspection, detection, and analysis of objects and conditions. Among the widely used algorithms are Scale-Invariant Feature Transform (SIFT) and Speeded-Up Robust Features (SURF), both of which are essential for feature detection and matching [11]. SIFT is both a key point detector and descriptor, primarily used for detecting and describing local features in images. It is highly effective in identifying objects regardless of image scaling and rotation. The SIFT algorithm follows several steps [11]:

1. Scale Space Construction: Creating internal representations of the image to ensure scale invariance.

2. Approximating Log: Using the Laplacian of Gaussian to find key points in an image.

3. Search for Key Points: Identifying key points by calculating maxima and minima from the difference of images.

4. Elimination of Key Points: Removing key points in edges and low contrast regions to improve efficiency.

5. Orientation Assignment: Calculating orientation for each key point to ensure rotation invariance.

6. SIFT Feature Generation: Generating unique representations to identify features effectively.

The efficiency and robustness of SIFT in feature detection make it a valuable tool in industrial applications, particularly in monitoring object positions and detecting anomalies [11].

SURF is another popular algorithm used in computer vision for object detection. It is known for its speed and robustness, making it suitable for real-time industrial applications [11]. The SURF algorithm involves:

1. Key Point Detection: Ensuring key points are scale and rotation invariant by examining corners and blobs.

2. Orientation Assignment: Aligning images based on the correct orientation of key points.

3. Descriptor Computation: Extracting key point descriptors to find similarities between images.

SURF's ability to rapidly detect and describe key points makes it ideal for monitoring moving objects and detecting tool wear and breakage in industrial environments.

For instance, the beverage manufacturing industry has seen substantial benefits from implementing vision-based defect detection systems. These systems are essential for maintaining high product quality standards, as stipulated by the International Organization for Standardization (ISO) 9001, which demands continuous quality improvement to satisfy customer expectations [12].

To further explore the role of image processing in quality control, the following section delves into specific algorithms designed for defect detection. These techniques are crucial for identifying anomalies such as tool wear, breakage, and other defects in manufacturing components, ensuring the integrity and reliability of industrial processes.

### **2.2.2. Image Processing Algorithms for Defect Detection**

Image processing has also become an integral part of quality control. Industrial settings require robust techniques to detect anomalies such as tool wear, breakage, and defects in manufacturing components. Various image processing techniques have been proposed and implemented for defect detection in industrial applications. These include adaptive thresholding, gray level co-occurrence matrices, morphological operations, and Otsu's thresholding [12]. Below, some specific adaptations of these techniques are discussed.

#### ***I. Wavelet and Fourier Transform Techniques:***

Abdel-Qader et al. [9] utilized wavelet transform, Fourier transform, Sobel filter, and canny filter for defect detection in concrete structures. Similarly, Hutchinson et al. [13] combined canny filter and wavelet transform to enhance defect detection accuracy in civil engineering applications. These techniques emphasize the importance of multi-scale analysis in detecting fine details and discontinuities in images.

#### ***II. Edge Detection and Morphological Operations:***

The paper by Alami et al. [14] presents an algorithm for defect detection in industrial pipes using Sobel edge detection, which highlights sharp changes in image intensity, essential for identifying defects like cracks and holes. Morphological operations are then applied to refine the detected edges, eliminate noise, and connect disjoint elements, thereby improving the reliability of defect identification.

#### ***III. Color Space Transformations and Clustering:***

Wu and Bai [15] proposed an image processing method based on HSV color space and Quick Fuzzy C-Mean (QFCM) clustering for defect feature extraction in buried pipelines. This method leverages color space transformations to enhance contrast and apply clustering techniques to segregate different defect types.

#### ***IV. Advanced Morphological Segmentation:***

Tung-Ching Su et al. [16] developed a morphological segmentation technique based on edge detection for sewer pipe defects, which can detect various anomalies like fractures, debris, and joint issues. Although their method was primarily for underground pipes, the principles of morphological segmentation can be adapted for industrial applications where precise defect classification is required.

### **2.2.3. Physical Inspection**

Shape inspection is another crucial aspect of quality control in industrial applications, and it sub-categories into three different section, Shape Inspection, Colour Inspec-

tion, Level Inspection. Different methods have been developed to evaluate shape features and detect defects. For example, Ramli et al. [17] proposed a partial erosion-based technique combined with a multilayer perception neural network for plastic bottle shape classification, achieving over 80% accuracy. This method involves morphological and erosion processes to segment the bottle shape and extract features, although it can be inefficient if the erosion parameters are not optimally set [12]. Similarly, Moradi et al. used the statistical histogram-based fuzzy C-means (SHFCM) algorithm to identify defects in apples. This method involves converting RGB images to Lab color space and using an active contour model for segmentation, achieving 96% accuracy for healthy apples and 91% for defective ones [18]. While effective, this technique is complex and prone to misclassification [12].

Color inspection is another critical component, especially in the food and beverage industry. Techniques like region growing and fuzzy c-means (FCM) have been used to enhance color image segmentation. Tang [19] proposed a region growing technique to segment color images by converting them to a specific color range and applying watershed techniques, although this method can be time-consuming and prone to over-segmentation. Wang et al. recommended combining FCM with support vector machines (SVM) to improve segmentation accuracy, particularly in complex color images [20].

Level inspection ensures that products, especially liquids, are filled to the correct levels. Automated systems can measure the liquid level in containers accurately, reducing the likelihood of underfilled or overfilled products. Advanced image processing techniques can detect the meniscus level and compare it to predefined standards, ensuring compliance with industry regulations [12].

### 2.3. CNC Technology

Numerical Control technology as known today, emerged in the mid-20th century. It can be traced to the year 1952, the U.S. Air Force, Massachusetts Institute of Technology in Cambridge, MA, USA, and the name of John T. Parsons (1913-2007), who is closely associated with the invention of numerical control as depicted in Fig.1 [21]. Numerical Control can be defined as an operation of machine tools employing specifically coded instructions to the machine control system [21].

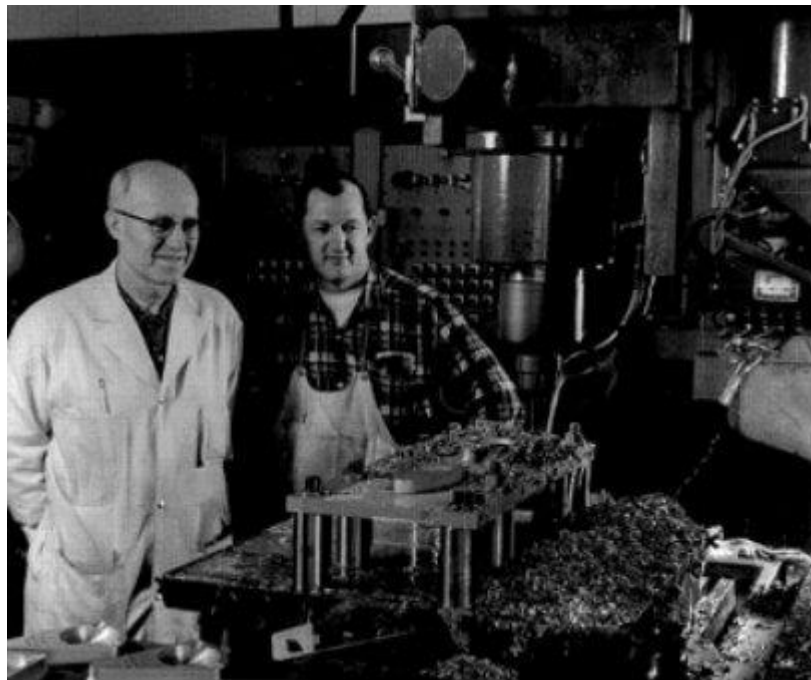


Figure 1. John Parsons, the inventor of the Numerical Controlled machine

This technology was not applied in production manufacturing until the early 1960's. The real boom came in the form of CNC, around the year of 1972, and a decade later with the introduction of affordable microcomputers [21]. In the manufacturing field, particularly in metalworking, Numerical Control technology has caused something of a revolution. Even in the days before computers became standard fixtures in every company and many homes, machine tools equipped with Numerical Control system found their special place in many machine shops [21]. The relatively recent evolution of microelectronics and the never-ceasing computer development, including its impact on Numerical Control, has brought enormously significant changes to the manufacturing sector in general and the metalworking industry in particular. These early numerical control developments were principally for the aerospace industry, where it was

necessary to cut complex geometric shapes such as airframe components and turbine blades [22].

The early to mid-1970s was a time of revolutionary advancement in the area of machine tool controller development, when the term CNC became a reality [22]. The multiple benefits of cheaper electronics with greater reliability have resulted in the CNC fitted to the machine tools of today, with their power and sophistication progressing considerably in the last few years, allowing an almost AI to the latest systems.

### ***2.3.1. Advances in CNC***

The evolution of CNC technology marks a transformative phase in manufacturing, driven by a quest for higher precision, efficiency, and integration with innovative technologies such as the IoT and automation systems. This evolution from manually operated equipment to advanced automated systems highlights CNC's pivotal role in modern manufacturing environments [23].

Historically, CNC machines have transitioned from simple mechanical systems to highly sophisticated units equipped with advanced computing capabilities. This evolution is characterized by significant improvements in tool accuracy, speed, and the ability to perform complex machining tasks. Key advancements include the adoption of remote monitoring systems and the integration of IoT, which enhance operational oversight and data management [23]. The incorporation of automation has dramatically transformed CNC machinery by minimizing human intervention while maximizing efficiency and precision. IoT advancements have furthered this transformation, allowing for machines to be connected and managed remotely, which is crucial for real-time monitoring and control. This technology enables wireless sensor networks that enhance system reliability by reducing potential failure points [23].

CNC technology has also embraced modern standards such as ISO 14649, also known as STEP-NC, which facilitates advanced data exchange and interoperability between computer-aided technologies (CAx) and CNC machines. This standard enhances controller functionalities to accommodate more complex and precise operations, pivotal in today's manufacturing standards. Additionally, technologies like the Web Ontology Language (OWL) for semantic data management and augmented reality for interfacing have been integrated to improve operational efficiency and flexibility [24-27].

Practical implementations of these advanced systems demonstrate significant benefits, including enhanced flexibility and interoperability through PC-based control-

lers and custom software modules. The integration of augmented reality and cloud computing has bridged the gap between digital planning and physical manufacturing, optimizing the learning curve and operational efficiency [27-29].

Zhu and Zhang [39] introduce a smart CNC machining monitoring system embedded within a Cyber-Physical Production Systems (CPPS) framework, which integrates both the physical and virtual aspects of CNC machines. A sample CPPS structure is shown in Fig.2, this framework consists of control, network, and decision layers, each crucial for the system's functionality, allowing for real-time data transmission and process adjustments. The implementation of CPPS not only improves the precision and efficiency of the machining process but also significantly reduces downtime and enhances productivity, which is particularly crucial in the production of complex parts requiring high geometric precision and surface integrity [31-34].

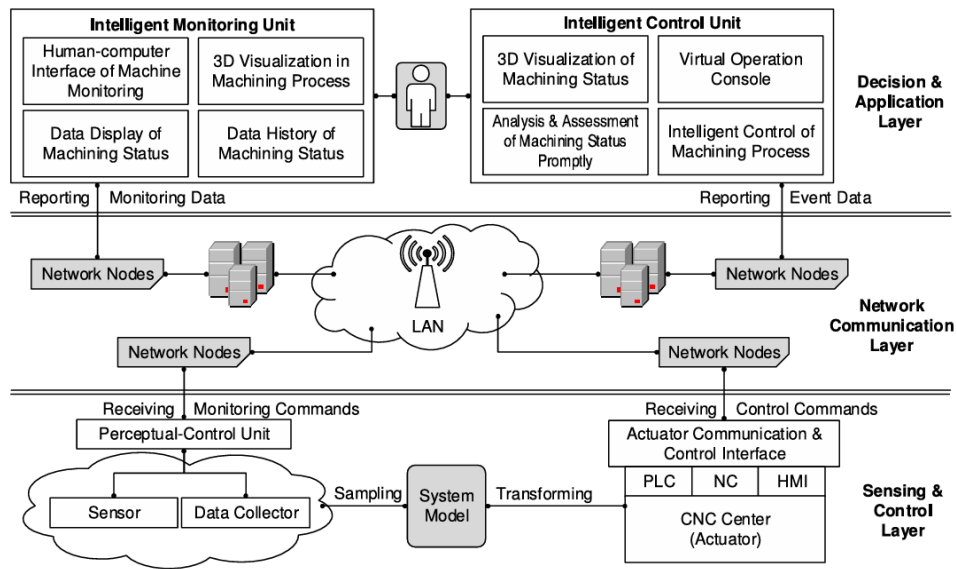


Figure 2 - Smart Machining Monitoring CPPS system structure. [39] © 2018 IEEE.

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## **2.4. Tool Condition Monitoring (TCM)**

### **2.4.1. Introduction to TCM**

TCM is a method used in various metal removal processes, including but not limited to turning, milling, and drilling [2]. TCM is essential for maintaining the high quality and precision required in advanced CNC machining applications such as aerospace and optics. The development of TCM has greatly benefited from advancements in sensing technologies and the integration of digital techniques, transforming the machining process into a more data-intensive operation.

A critical challenge faced by manufacturers is ensuring both minimized maintenance costs and augmented reliability of their manufacturing equipment [35]. Within this context, there is a paramount need to extend the service life of cutting tools, avoiding premature replacements and sidestepping potential scrap incidents resulting from tool breakages [35]. These demands underscore the growing necessity for a transition from traditional maintenance approaches to condition-based ones, emphasizing the value of robust, adaptive, and efficient TCM methods [35].

Understanding the evolution and integration of advanced TCM systems is critical for appreciating the significant improvements they bring to CNC machining. To fully grasp the transformative impact of these innovations, it is essential to compare traditional and modern TCM techniques. This comparison will highlight the advancements that have redefined tool condition monitoring, showcasing the benefits and limitations of each approach.

### **2.4.2. Comparison of Traditional and Modern Techniques in Tool Condition Monitoring**

The evolution of TCM has seen a shift from traditional methods to more advanced, data-driven techniques. Traditional methods, primarily direct measurement techniques, have involved the use of touch probes, optical instruments like Charge-Coupled Device (CCD) cameras or optic sensors, and other direct contact methods to assess the wear and condition of tools. These methods often yield precise results by directly measuring dimensional changes in the tool or machined part. However, they require interruption of the machining process, which can adversely affect productivity. In contrast, modern TCM techniques leverage a variety of sensors and data-driven models to perform indirect monitoring without stopping the machine. These sensors collect data on vibrations,

acoustic emissions, cutting forces, and temperature, providing a comprehensive view of tool health in real-time [8].

- **Sensor Technology:** Advances in sensor technology allow for the continuous collection of data. For example, accelerometers and dynamometers are less intrusive and can operate under the harsh conditions of machining environments [8].
- **Computational Intelligence:** The integration of machine learning, particularly techniques like Support Vector Machines and Artificial Neural Networks (ANN), has transformed TCM by enabling the analysis of complex data patterns that predict tool wear [34, 36]. These methods significantly improve prediction accuracy over traditional techniques.
- **Industry 4.0 Compatibility:** Modern TCM systems align well with Industry 4.0 by facilitating predictive maintenance and minimizing unplanned downtimes, thereby enhancing overall productivity and reducing operational costs [8].

Modern methods are preferable due to their non-intrusive nature and continuous monitoring capability, which do not disrupt the manufacturing process. The use of deep learning and AI technologies, like Convolutional Neural Network (CNN) and Deep Multi-Layer Perception (DMLP), provides superior predictive performance by analyzing vast amounts of operational data to detect subtle patterns associated with tool wear and failure [8, 37].

While modern techniques offer substantial benefits, their implementation comes with challenges. These include the need for high initial investment in sensor technology and computational infrastructure, the complexity of integrating these systems into existing manufacturing setups, and the reliance on large volumes of high-quality training data for machine learning models to function effectively [8]. Also, data acquisition and processing methods face challenges due to the vast data influx [38], necessitating novel models and frameworks to manage and utilize "big data" for optimizing machining processes [31]. The challenges are primarily due to the need to accurately assess tool states amidst a vast array of data, necessitating novel models and frameworks that effectively manage and utilize "big data" to optimize machining processes [31]. To address these challenges, recent innovations in TCM have introduced models that utilize big data analytics, deep learning, and heterogeneous data fusion. Such models represent a significant evolution from traditional systems that relied on simpler signal processing and basic AI

techniques. As Zhu et al. (2018) articulate, these advancements not only enhance machine tool performance but are crucial for the realization of intelligent manufacturing systems [38, 39].

Historically, the primary techniques for monitoring tool condition in CNC machines have broadly been categorized into direct and indirect methods [40]. Indirect methods, derive tool condition from various types of machine-generated data. Techniques like Acoustic Emission (AE) monitoring and force analysis fall under this category. AE methods have the advantage of being highly sensitive and can provide rapid feedback [41]. However, their efficacy is often compromised by environmental noise, leading to potential false positives or missed detections of tool wear and breakage [42]. Furthermore, the interpretation of AE signals can be complex, as they can be influenced by various factors such as cutting conditions, material properties, and machine tool dynamics [43]. Force analysis has been another widely used method for monitoring tool wear and breakage in CNC machining processes. By measuring cutting forces or torque during the machining process, this technique can provide valuable insights into the condition of the cutting tool. Typically, both cutting forces and torque tend to increase as the tool wears, and any sudden changes in these parameters can indicate tool breakage or other issues [44]. Force analysis, while a traditional staple in tool condition monitoring, are relatively expensive and have certain disadvantages that limit their effectiveness in detecting tool wear and breakage. The accuracy of these systems can be affected by a range of factors, including variable cutting conditions such as different tool diameters (e.g., 1 mm, 10 mm, or 100 mm), which result in a wide range of cutting forces, and the dynamic nature of the machining process itself, making it challenging to precisely identify tool wear or damage [42]. In addition, the calibration and setup of these sensors can be time-consuming and complex, potentially leading to inaccuracies and inconsistencies in the monitoring process.

#### ***2.4.3. Artificial intelligence in TCM***

During the early stages of TCM research that utilized classical AI methods, there were significant constraints regarding the quality and volume of data [7]. Classical techniques such as ANN, SVM, and fuzzy clustering were previously adequate for the limited data from these processes. However, they lacked the accuracy and adaptability required to cater to changing conditions and operational parameters during machining [7].

Classical AI techniques soon became inadequate for the task of processing this volume of data. Deep learning algorithms, having shown immense success in various fields like autonomous driving and medical imaging, began to emerge as potent solutions for TCM in this new environment of big data [7]. However, the challenges related to data for deep learning applications are evident. With high experimental costs and intensive labelling requirements, strategies such as regression to finely labelled data have been proposed to produce synthetic data to meet deep learning's large dataset necessities [37]. The challenges persist, notably in selecting the right deep learning method for a specific machining process. The success of these methods often depends on the quality of the processed signal which feeds the deep learning algorithm [7]. The choice of feature selection, extraction, and signal transformation methods plays a pivotal role in ensuring a high-performance system.

A noteworthy mention is the distinct behaviour of metal cutting methods. Interrupted processes like milling offer more detailed insights into the tool's state or mode of wear. Leveraging deep learning can effectively detect this intricate information, provided the appropriate signal transformation technique is applied [7]. However, this approach can sometimes lead to increased data sizes, presenting processing and storage challenges [7].

Recent advancements in AI and DL have significantly enhanced the effectiveness of indirect methods for tool condition monitoring. A comprehensive review of these advanced methodologies and their applications in this context is done by G. Serin et al. [45]. These technologies offer sophisticated analysis capabilities that were previously unattainable. Nevertheless, the implementation of these solutions in real-world manufacturing settings is not without its challenges. Issues such as the integration of DL models with existing CNC machinery, the high cost and complexity of deployment, and the 'black box' nature of DL models pose significant barriers. Moreover, the scalability and adaptability of these solutions across different machine types and environments remain limited, often requiring extensive customization and retraining.

Direct methods, in contrast, primarily focus on physical measurements and can be further classified into two subcategories: contact and non-contact methods. Contact methods typically employ devices such as touch probes, which directly interact with the machine components to assess tool dimensions and integrity. While these methods are known for their high precision, they often fall short in detecting more nuanced forms of tool damage, like edge fractures or wear. Moreover, they can be considerably time-

consuming as they necessitate halting the machining process for measurement, requiring the tool to go to a specific position and then return after the measurement, thereby contributing to the total downtime. Such delays can lead to significant inefficiencies, especially in fast paced manufacturing environments. Non-contact direct methods, which utilize visual sensors, cameras, and image processing techniques, have been garnering increased attention in recent years [46]. Machine vision and image processing techniques are highly effective for monitoring tool wear and breakage. For instance, a study by Peng et al. [47] proposed an automatic tool wear monitoring system based on machine vision, using the wear area of the flank face as a new evaluation index. It showed promising results for tool wear monitoring with an error rate of 5.63% when compared to values obtained from microscopic experiments, meeting industry requirements. Kratochvil and Cermak [48] developed a low-cost tool breakage detection system for CNC machining, using the OpenCV library and a digital camera. This system aims to efficiently detect tool breakage, especially in the machining of materials like plywood and fiberglass, thereby enhancing production efficiency in small CNC machines. While direct methods utilizing image processing have shown promising results, they remain an underexplored area with significant potential for further development. This research introduces a novel, camera-based TCM system designed for efficiency and practicality. By utilizing a standard camera phone for high-resolution video recordings, coupled with basic image processing techniques—frame extraction, background subtraction, thresholding, and morphological operations—this approach effectively facilitates real-time tool breakage detection. Moreover, it enables the near real-time identification of edge fractures, a capability not extensively explored in previous methods. The integration of an everyday device like a camera phone highlights the system's accessibility and cost-effectiveness, aligning it with the practical needs of modern manufacturing environments.

## 2.5. Role of Cameras in CNC Machining and Tool Monitoring

The integration of cameras into CNC monitoring systems has significantly advanced the ability to inspect tool in real-time. Cameras, particularly those based on machine vision, provide a direct method of monitoring by capturing detailed images of the tool conditions [49].

Kratochvil and Cermak [50] propose an economical tool breakage detection system using the OpenCV library and a digital camera. The system utilizes an ARM-based computer or an x86-64 system running Raspbian OS and is implemented in Python for cross-platform compatibility and ease of modification [51]. It employs a CCD/CMOS camera with a resolution of at least 640x480, capable of withstanding vibrations, and LEDs to enhance tool visibility. Image processing techniques, including grayscale conversion, Canny edge detection, Gaussian pyramids, and Hough transformation, are used to detect tool edges. This low-cost, open-source solution is practical for small CNC machine operators facing frequent tool breakages. However, it is only effective for detecting breakages and cannot address other issues such as tool wear or fractures.

Jianbo Yu et al. [52] present a machine vision-based method for measuring chisel edge wear in drills. Their approach uses advanced image processing techniques like local variance threshold segmentation, bidimensional local mean decomposition (BLMD), and adaptive contrast enhancement. An adaptive median filter removes salt-and-pepper noise, while BLMD enhances image contrast by decomposing the tool image into high- and low-frequency components. Validated through experiments with a 15/64-inch drill, CMOS industrial camera, and three-color light source, the method accurately measures wear by counting pixels in the wear area [52]. While this method improves accuracy and efficiency, it has limitations. It primarily focuses on chisel edge wear and may be less effective for other tool wear types or different machining conditions. Additionally, the experimental setup may be challenging to implement in industrial environments with limited space and resources.

Cyber-Physical Systems represent a paradigm shift in manufacturing, integrating software and hardware to control physical processes in real-time [53]. CPSs are distinct from traditional systems due to their decentralized architecture and ability to dynamically adapt to environmental changes [54]. The integration of machine vision into CPS for tool condition monitoring offers several benefits, including increased accuracy, reduced downtime, and enhanced predictive maintenance capabilities [55]. The modular nature

of CPS allows machine vision systems to be easily integrated into existing CNC machines, enhancing their capabilities without significant overhauls. However, integrating machine vision systems into heterogeneous manufacturing environments requires meticulous planning and standardization of communication protocols and data formats [54]. Also the initial investment in high-resolution cameras and advanced image processing software can be substantial, though the long-term benefits often justify the costs. Addressing the challenges of integration and environmental variability will be crucial for maximizing the potential of these systems in future manufacturing processes.

The integration of image processing and artificial intelligence (AI) techniques, particularly neural networks, has shown promising advancements in this area. Jammu et al. [55] employed unsupervised neural networks for tool breakage detection using sensor-assisted images, highlighting the potential of machine vision in direct measurement techniques. Pfeifer and Wiegers discussed the advantages of machine vision, emphasizing its reliability in tool wear measurement [56]. Castejón et al. utilized computer vision systems to analyze 1383 images obtained from a CNC parallel lathe, successfully estimating the wear level in cutting inserts [57]. Similarly, Barreiro et al. studied different moments to describe tool-wear images and classify tool conditions, demonstrating the utility of geometric descriptors in wear monitoring [58]. Artificial Neural Networks (ANNs) have become a prevalent AI technique in predicting tool wear and tool life in CNC machining. ANNs can model the complex relationships between input process data and output wear parameters, providing accurate predictions of tool life. Ezugwu et al. used ANNs to predict tool life and failure modes in turning operations, achieving a high correlation between predicted and actual tool wear [59]. The paper by Mikołajczyk et al. explores a two-step method combining neural networks and image processing to predict tool life in turning operations, providing an automated solution that meets industrial requirements [60]. This approach was further validated using the Neural Wear software, which estimated the VB parameter from images, confirming the potential of combining image recognition software with ANN models for low-cost tool life estimation. Several studies have compared different methodologies and techniques for tool wear prediction. Attanasio et al. compared Response Surface Methodology (RSM) with ANN fitting techniques, finding that ANN models provided better approximations in predicting tool-wear parameters [61, 62]. Yiqiu et al. tested Support Vector Machines and found them to have better generalization capabilities compared to ANN models when using texture features of the surface as inputs [63].

Recent innovations have focused on enhancing the accuracy and reliability of these AI-based models. For example, D'Addona et al. developed an ANN for automatic tool-wear recognition using cognitive paradigms, further demonstrating the robustness of ANNs in industrial applications [64, 65].

### 3. METHODOLOGY

#### 3.1. Equipment and Setup

This study utilized a consumer-grade camera, specifically an iPhone 12 Pro, selected for its capability to record at 60 frames per second and in 1080p resolution. Although the iPhone 12 Pro was chosen for its availability, the methodology is applicable to any camera meeting these specifications. The camera was mounted on a tripod for stability and positioned to capture the tool at the CNC machine's changing position (Fig. 2), where tools are automatically exchanged via a Programmable Logic Controller (PLC) system. The CNC machine used in this experiment is equipped with multiple tool options, such as chamfer makers, hole makers, drillers, and cutters, facilitating a diverse range of machining tasks.



Figure 3 - Camera and tripod inside the CNC cabin.

#### 3.2. Initial Approach: Using YOLOv8 for Tool Detection and Segmentation

Before arriving at the current image processing-based approach, an initial methodology was attempted involving the use of YOLOv8 (You Only Look Once, version 8) algorithm to train a model for detecting and segmenting CNC tools. YOLO is a popular deep

learning model used for object detection due to its speed and accuracy in identifying objects within images. The YOLO family of models operates by dividing the input image into a grid and predicting bounding boxes and class probabilities directly from the image in a single evaluation, making it extremely fast and efficient for real-time applications [85]. YOLOv8, the latest version, brings several improvements over its predecessors, including enhanced architecture, better accuracy, and more robust performance in detecting and segmenting objects in complex scenes [85]. The plan was to use YOLOv8 to segment the tool in images and then calculate the area of the segmented region to assess the tool's condition.

### **3.2.1. Training The YOLOv8 Model**

- *Dataset Collection:* The initial step involved collecting a dataset of images containing various CNC tools in both intact and broken states. Each image was annotated to mark the boundaries of the tool, creating a labeled dataset for training. A sample of the data can be seen in Fig. 4.

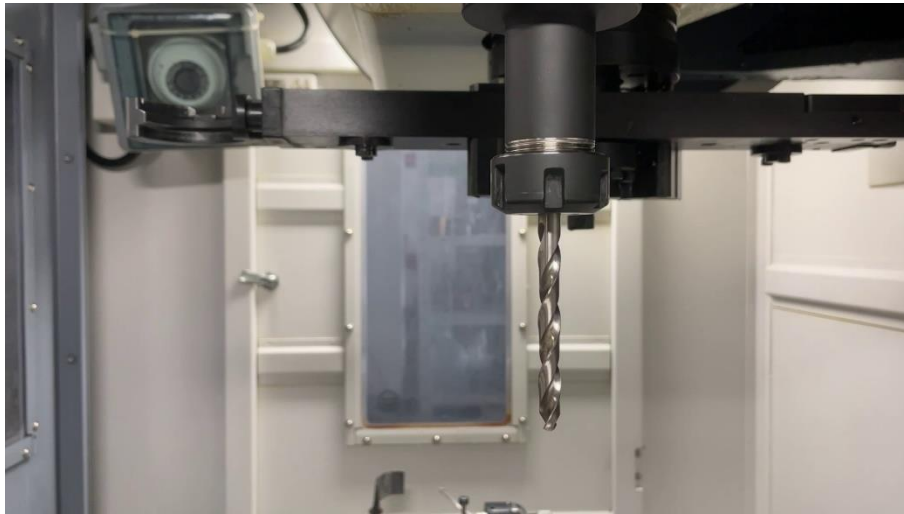


Figure 4 – Sample data used for training the YOLOv8 model.

- *Annotation Process:* Each image was annotated to mark the boundaries of the tool, creating a labeled dataset for training, as seen in Fig. 5

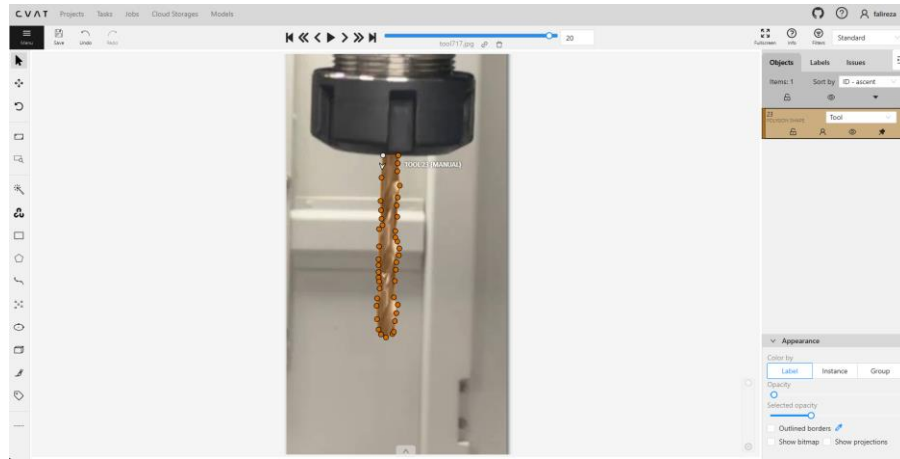


Figure 5 – Sample manually annotated data for training the YOLOv8 model.

- ***Model Training:*** The YOLOv8 model was trained on this dataset to learn to detect and segment the tools from the background.

However, the YOLOv8 model was not successful. One of the primary challenges was the infinite number of ways a tool can break. Unlike intact tools, which have a consistent shape, broken tools can exhibit numerous fracture patterns, making it difficult for a model to generalize from a limited dataset.

### 3.2.2. Refinements

#### 3.2.2.1. Using edge detection

The complexity of detecting tool edges against varying backgrounds proved to be a significant hurdle. The model often struggled to accurately segment the tool, especially when the contrast between the tool and the background was low. Therefore, it was decided to initiate Canny edge detection on the dataset and then attempt to annotate the model and train the data. Canny edge detection is a popular edge detection algorithm that uses a multi-stage process to detect a wide range of edges in images [51]. It involves steps such as noise reduction, gradient calculation, non-maximum suppression, and edge tracking by hysteresis to produce a binary image with detected edges [51]. A sample frame after edge detection is shown in Fig. 6.

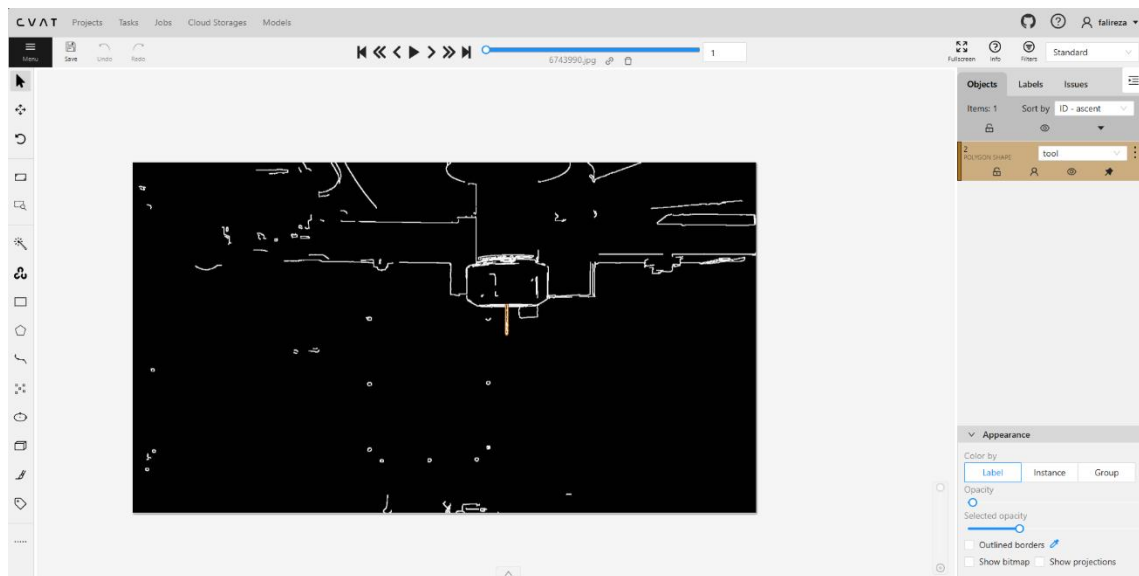


Figure 6 - Sample annotation after Canny edge detection.

However, as the tools became smaller, the Canny edge detection algorithm failed to accurately identify the edges, resulting in overlapping curves. For smaller tools (e.g., 1 mm in width), the sides of the tool tended to connect, as illustrated in Fig. 7.



Figure 7 - Annotation sample of smaller tools. The width of the tool is so small (1 mm) that Canny edge detection fails to correctly identify the edges, causing the tool to appear as a single edge.

Due to these issues, another refinement involving background adjustment was attempted.

### 3.2.2.2. Background Adjustment

To address the issue of correctly detecting the edge of the tool against the CNC machine's neutral-colored background, a corrugated fiberboard was placed in the back-

ground to enhance the tool's visibility. The textured surface of the fiberboard was intended to provide a more distinct contrast, aiding in solving the low contrast problem. Two samples of data on various tools can be seen in Fig. 8.



Figure 8 - Two different types of tools with a fiberboard background.

These images were then manually annotated to prepare for the YOLOv8 model. A sample of manual annotation with the fiberboard background can be seen in Fig. 9.

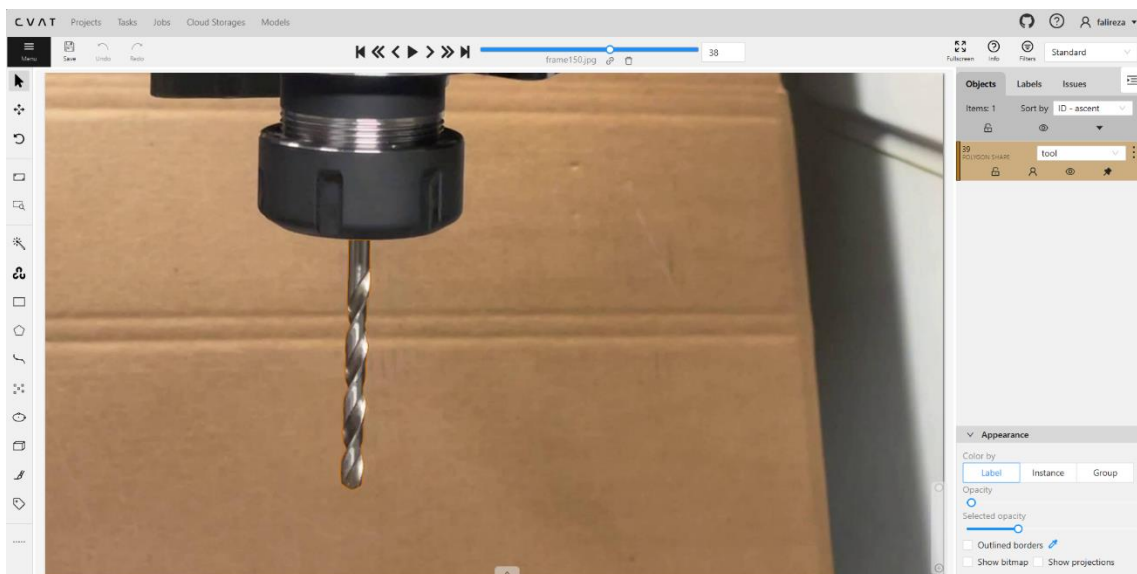


Figure 9 - Sample of manual annotation with a fiberboard background.

These annotated images were directly fed into the YOLOv8 model with the hope of training a model that could accurately identify the edges and perform segmentation. Unfortunately, the model still faced problems. The result graph and the loss function of the trained model can be seen in Fig. 10.

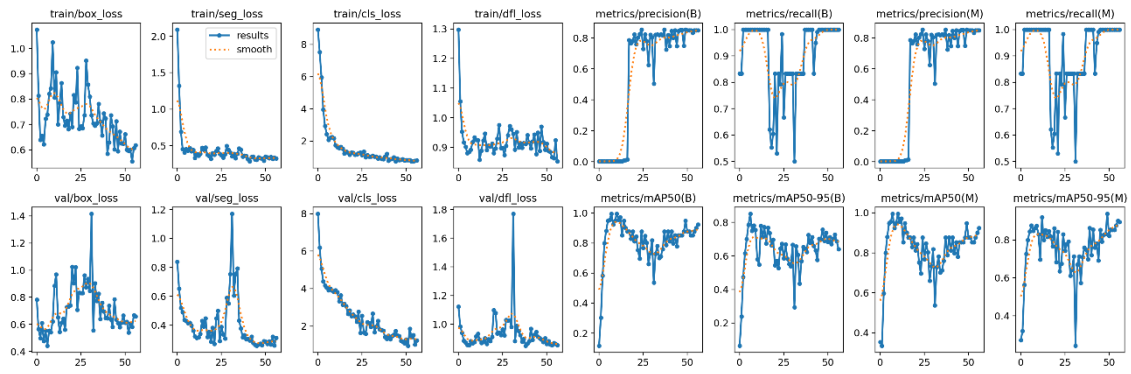


Figure 10 - Training graphs of the YOLOv8 model with the fiberboard background, showing occasional anomalies but generally converging loss function.

The predictions of the model after training are illustrated in Fig. 11.

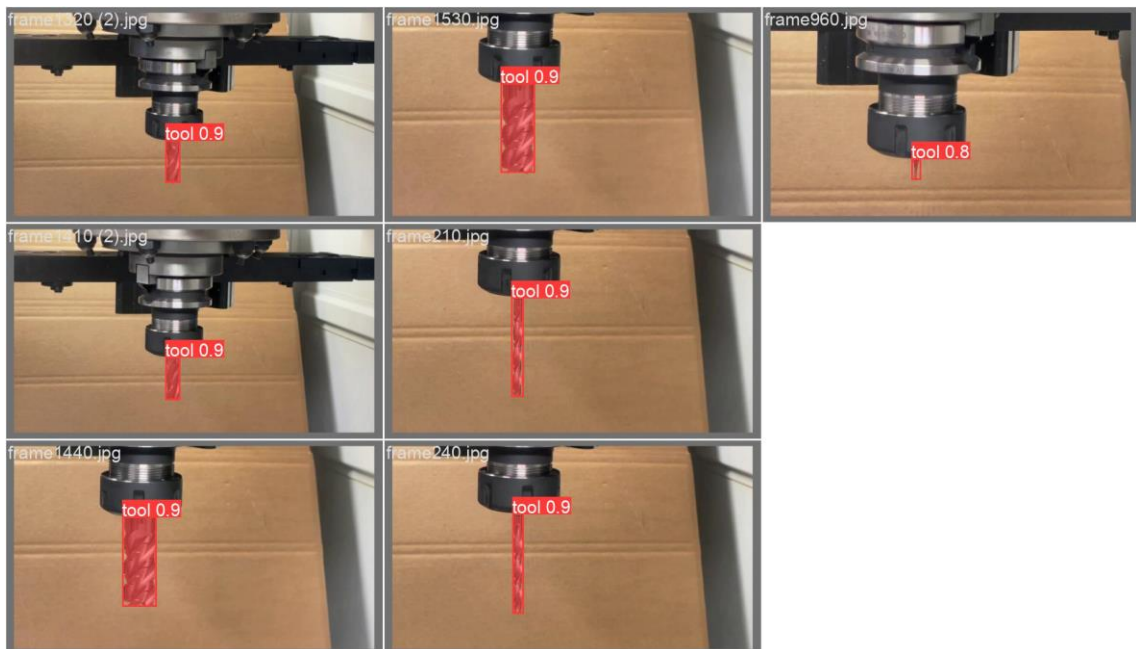


Figure 11 - Model predictions after training on new data.

However, as seen in frame210.jpg, there was still a problem with correctly identifying edges. A larger view of frame210.jpg can be seen in Fig. 12.



Figure 12 - Model predictions showing issues with edge identification in frame210.jpg.

### 3.2.3. Conclusion

- Model Uncertainty: Training a deep learning model like YOLO involves inherent uncertainty. Even with a well-annotated dataset, the model's performance can vary, making it challenging to achieve consistent and reliable results across all tool types and breakage patterns.
- Extensive Data Requirements: Training a robust model requires a large and diverse dataset. This includes numerous examples of each tool type in both intact and broken states. However, many CNC tools are expensive, and access to a wide variety of broken tools for training was limited. Ideally, training such a model would necessitate at least 50 different broken and fractured scenarios for each tool type, which was not practical.

Given these challenges, the YOLO-based approach was deemed impractical for the specific requirements of tool condition monitoring in CNC machines. The extensive data collection needed, the complexity of segmentation in varying backgrounds, and the infinite patterns of tool breakage made this method unsuitable for real-world applications.

### 3.3. Transition to a Traditional Image Processing Approach

It was concluded that a traditional image processing approach, which does not require model training, would be more reliable and feasible. This led to the development of the

current methodology that uses straightforward image processing techniques to detect tool breakage and fractures.

### ***3.3.1. Image Acquisition and Analysis***

Upon each tool's arrival at the changing position, two key processes are initiated: the immediate capture of a still image and a 6-second video recording at 10 RPM, ensuring a full 360-degree rotation of the tool. The still image is used to detect significant height differences that could indicate tool breakage, while the video assists in identifying fractures that do not alter the tool's height.

For clarity, four illustrative figures are provided to depict various tool conditions:

1. Fig. 13 displays an intact tool within its holder, serving as a baseline for optimal condition.



Figure 13 - Intact tool.

2. Fig. 14 shows a tool with visible breakage, where only the shank remains in the holder, illustrating significant loss of the working part.



Figure 14 - Broken tool.

3. Fig. 15 presents an unfractured tool, used to contrast with the fractured scenarios.



Figure 15 - Unfractured chamfer maker tool

4. Fig. 16 highlights a tool with an edge fracture, emphasizing the subtle but critical signs of potential failure.



Figure 16 - A chamfer making tool with an edge fracture.

### **3.4. Software and Image Processing Techniques**

Analysis of the acquired image and video frames employs the OpenCV library, renowned for its extensive application in computer vision projects the process for the still image involves:

#### ***3.4.1. Region of Interest (ROI) Identification***

The starting point for defining the ROI is the face of the spindle, which is unique and fixed in each CNC machine. This ensures that the ROI is consistently located across different operations and machine setups. Given the CNC machine's design, where the tool moves exclusively vertically, and the changing position remains constant, the ROI is predefined within the frame to include this critical area. Furthermore, the width of the ROI is determined by the tool change system, which means the dimensions of the ROI can be precisely defined for every CNC machine. This targeted approach significantly reduces the data volume for processing, focusing solely on the area around the tool, as shown in Fig. 17.

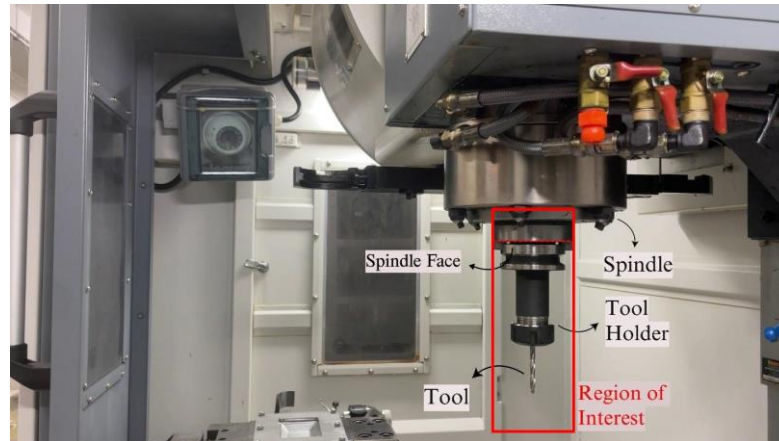


Figure 17 - Sample frame captured by the camera, highlighting the region of interest distinguished with dashed lines.

### 3.4.2. Background Subtraction

Initially, a reference frame is captured and stored, showcasing the tool slot's background without the presence of any tool or tool holder. This reference frame serves as a baseline for comparison. Subsequent images captured when the tool is in the changing position undergo a subtraction process from this stored background frame. This technique effectively isolates the tool's image, allowing for precise and focused analysis of its condition. Fig. 18 illustrates a sample result of this background subtraction process.

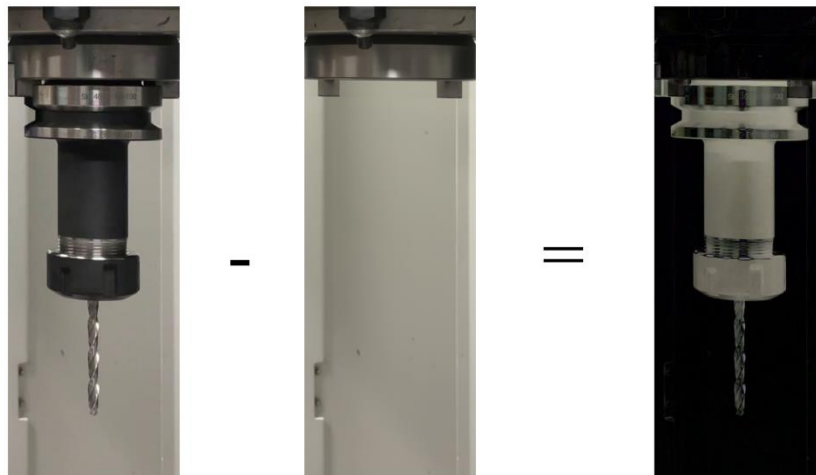


Figure 18 - Result of subtracting a sample frame from the reference background frame, isolating the tool for analysis.

### ***3.4.3. Grayscale***

The ROI is converted into grayscale to simplify the image by eliminating unnecessary colour data. This step reduces computational complexity and streamlines the subsequent analysis. The result of grayscale is shown in Fig. 19.



Figure 19 - Conversion to grayscale to simplify the image.

### ***3.4.4. Binary Thresholding***

Binary thresholding is applied to the grayscale image with an initial lower boundary of 30 to enhance the visibility of the tool against the background. This threshold value of 30 was determined through trial and error, aiming to strike a balance between eliminating the background and preserving the essential details of the tool. It is critical to acknowledge that the optimal threshold value is not universally fixed but rather depends on the specific illumination and lighting conditions of each CNC machine. Consequently, this parameter can and should be adjusted for each machine to achieve the best possible results across various tools and operating environments. Such adaptability ensures that the binary thresholding process remains effective and reliable, regardless of the diverse lighting conditions encountered in different CNC machining settings. The result of Binary Thresholding is shown in Fig. 20.

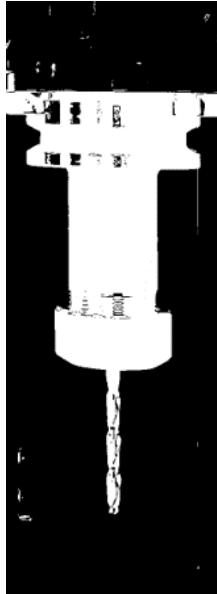


Figure 20 - Binary thresholding with a lower boundary of 30 to enhance tool visibility.

#### ***3.4.5. Morphological Closing***

Morphological closing is employed to refine the image further by closing small gaps within the tool's silhouette and removing isolated white pixels, enhancing the tool's distinction from the background. This step addresses artifacts introduced by binary thresholding, ensuring the tool's shape is accurately represented. The result of morphological closing is shown in Fig. 21.

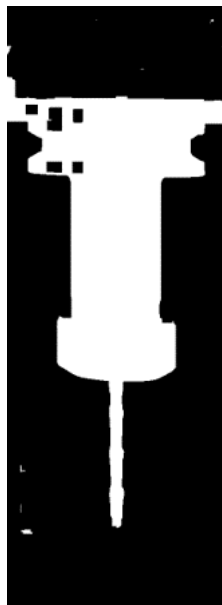


Figure 21 - Morphological closing to refine the tool's silhouette.

### **3.4.6. Contour Analysis**

Finally, contour analysis isolates the tool by identifying and retaining the largest contour, presumed to be the tool itself, while eliminating smaller, irrelevant contours. This step effectively removes any remaining noise, leaving a clean representation of the tool for breakage detection. The result of contour analysis and the final result of this subsequent image processing techniques is shown in Fig. 22. This visual representation underscores the effectiveness of each step in isolating and preparing the tool's image for detailed condition monitoring.

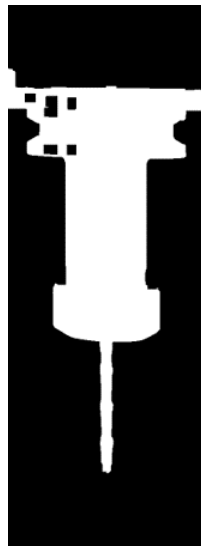


Figure 22 - Final result. Contour analysis was done to detect the largest contour.

### **3.5. Height Calculation**

To ascertain tool breakage, the system employs a straightforward and effective height measurement technique applied to processed images. Once the tool reaches the designated changing position, the initial frame captured undergoes various image processing steps as previously outlined, resulting in a binary image where both the tool and its holder are distinctly isolated from the background. To determine the tool's height, the system identifies the vertical span of white pixels that represent the tool. This process involves locating the first and last rows of white pixels within the image and calculating the pixel difference between these two points to yield the tool's height in pixels. Before monitoring the tools during operation, their initial heights are measured and stored in a database. This step is essential to create a reference point for future comparisons. It helps to detect any large deviations in height that show tool breakage. The system can

accurately identify broken tools by comparing the baseline height with the current height and finding significant reductions caused by damage.

### 3.6. Area Calculation

Beyond detecting tool breakage, the system's diagnostic capabilities extend to identifying tool fractures—a functionality that conventional contact-based methods cannot achieve. This process requires a meticulous examination of the tool's terminal segment, where the highest loads during machining often damage the cutting edge, typically confined to the final 2-3 times the tool's diameter. For the tools examined in this study, particular attention was given to the final 10 mm, critical for the machining operations, as illustrated in Figures 23 and 24 showing the tool at various degrees of rotation.

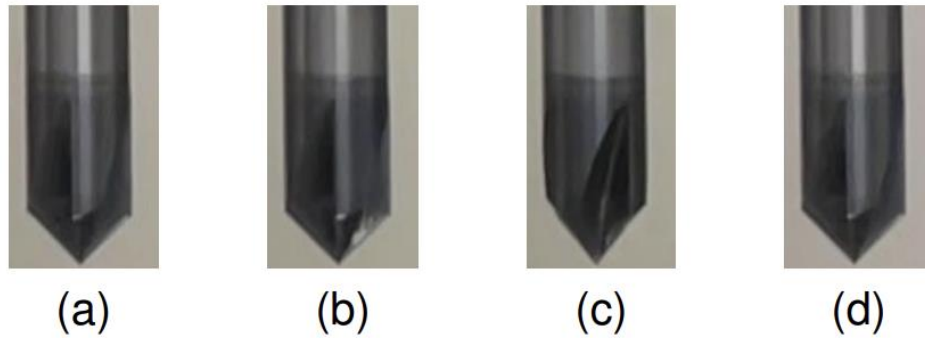


Figure 23 - Terminal region of the intact tool in the original frame at various degrees of rotation: 1°, 85°, 133°, and 360°.

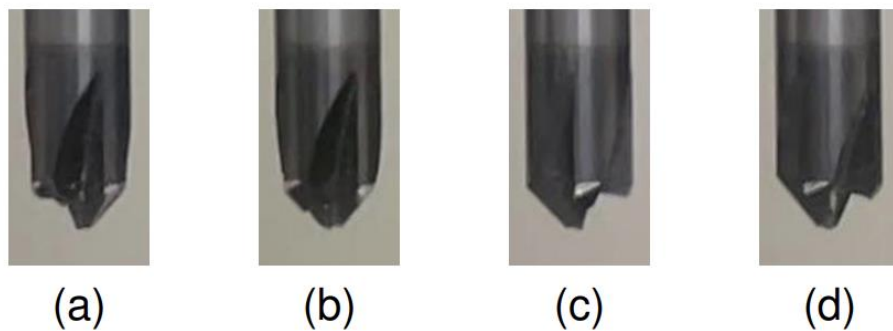


Figure 24 - Terminal region of the broken tool in the original frame at 1°, 85°, 133°, and 360° of rotation.

For each of the 360 frames representing a complete rotation of the tool, the system quantifies the total area represented by the tool in the image. This quantification is achieved by summing the number of white pixels within the specified terminal section

of the tool. Focusing on this critical area allows the detection of any irregularities, such as fractures, that could compromise the tool's functionality, by observing changes in the pattern of pixel distribution. These findings are depicted in the processed images in Figures 25 and 26, which showcase the terminal region of both intact and broken tools through various rotation degrees.

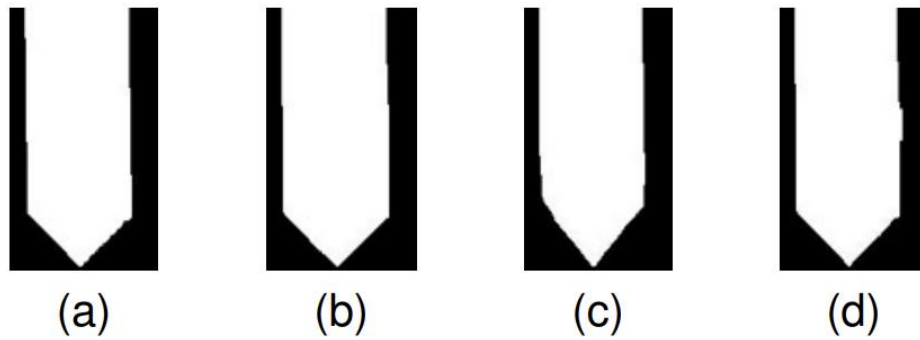


Figure 25 - Processed images showing the terminal region of the intact tool at 1°, 85°, 133°, and 360° of rotation.

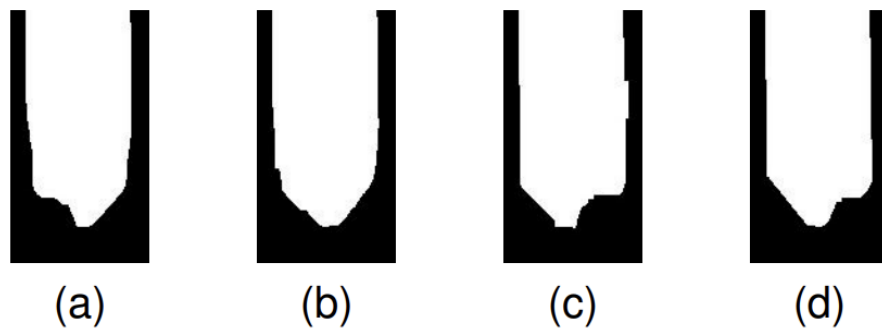


Figure 26 - Processed images showing the terminal region of the broken tool at 1°, 85°, 133°, and 360° of rotation.

It is important to note that the depth of the inspection area, typically 2-3 times the diameter of the tool, depends on the specific type of tool and its operational parameters. This adaptability enhances the system's capability to cater to a wide array of tools and machining strategies, emphasizing its utility and effectiveness in varied manufacturing environments.

With the methodological groundwork established, the following section will present the results obtained from applying these techniques. The findings will demonstrate the effectiveness of the proposed system in real-world CNC machining scenarios, highlight-

ing its potential to significantly improve maintenance strategies and operational efficiency.

## 4. RESULTS AND DISCUSSION

This section explores the outcomes of the methodologies developed for tool condition monitoring (TCM) within a CNC machining context. It emphasizes both the precision of the proposed approaches and their broader implications for implementation.

### 4.1. Tool Breakage and Grip Slip Detection

A critical capability of the proposed system is its ability to detect tool breakage, as demonstrated through a series of experiments. By calculating the tool's height in pixels from processed images, the system effectively identifies significant reductions in height that are indicative of breakage, as illustrated in Fig. 17.

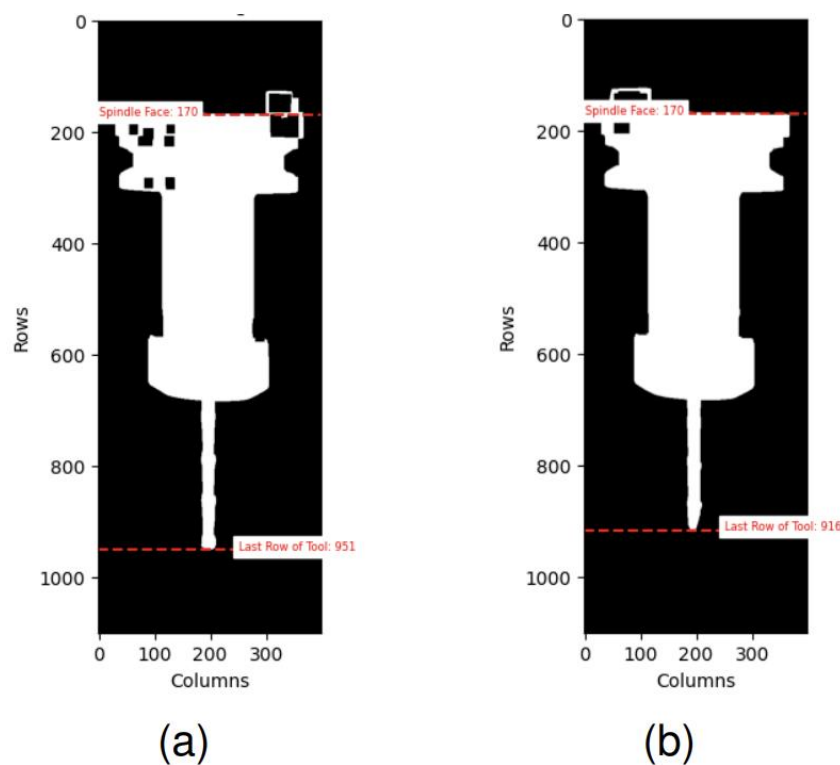


Figure 27 - Comparison of a tool in its (a) intact state and (b) broken state. The observed height difference of 35 pixels, corresponding to a 7 mm reduction, is indicative of tool breakage.

This method facilitates immediate and non-intrusive detection of tool breakage, presenting a substantial improvement over traditional contact-based measurement methods. These conventional methods typically necessitate machine downtime and direct physical access to the tool, thus highlighting the efficiency and practicality of the proposed system.

In addition to detecting tool breakage, another significant challenge in CNC machining is the slippage of the tool within its holder. This slippage does not necessarily result in visible damage to the tool itself but can lead to inaccuracies in machining, ultimately resulting in scrap and rework. This issue is particularly problematic because it is often difficult to recognize, especially in operations where only one tool is used for the entire machining surface, resulting in no visible inaccuracy even if the pocket depth varies by several millimeters. According to the cutting forces, the tool overhang will increase after the cutting process due to wear and tear, which amplify this issue. The proposed TCM system offers a potential solution to this slippery problem by closely monitoring the tool's position relative to its holder, the system can detect anomalies indicative of slippage. When tool overhanging changes, usually because the friction force in the tool holder (e.g., ER-collet) is not sufficiently high, the TCM system can provide notifications to change the tool holder to another type, such as a power grip toolholder. These power grip toolholders provide higher friction forces, offering an efficient solution to avoid slippage. However, these toolholders are more expensive and are recommended only for operations where slippage has already occurred or is highly likely.

## **4.2. Fracture Detection Analysis and Technological Considerations**

Expanding upon the breakage detection methodology, this section demonstrates the system's proficiency in identifying tool fractures through detailed analysis of the tool's terminal region. By graphically comparing intact and fractured tools, the system's diagnostic capability to discern discrepancies indicative of fractures is highlighted, as shown in Figures 18, 19, and 20.

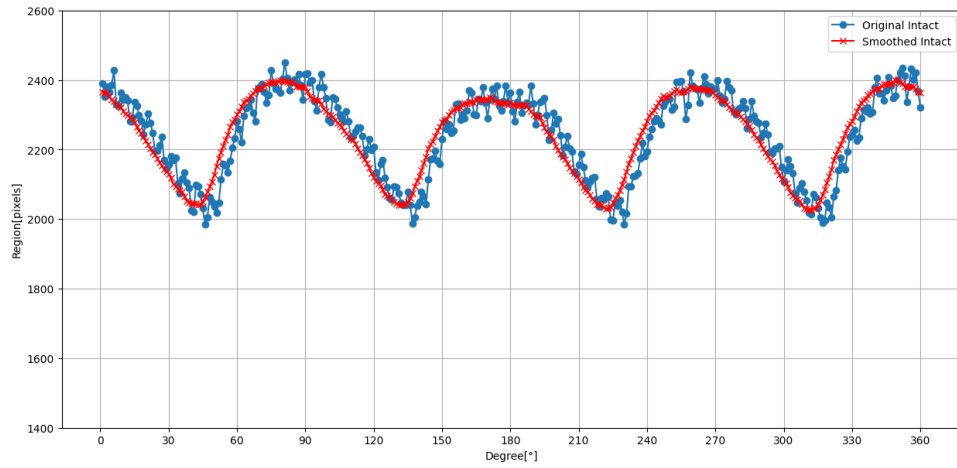


Figure 28 - Combined graph of the intact tool, illustrating the consistency in the tool's profile.

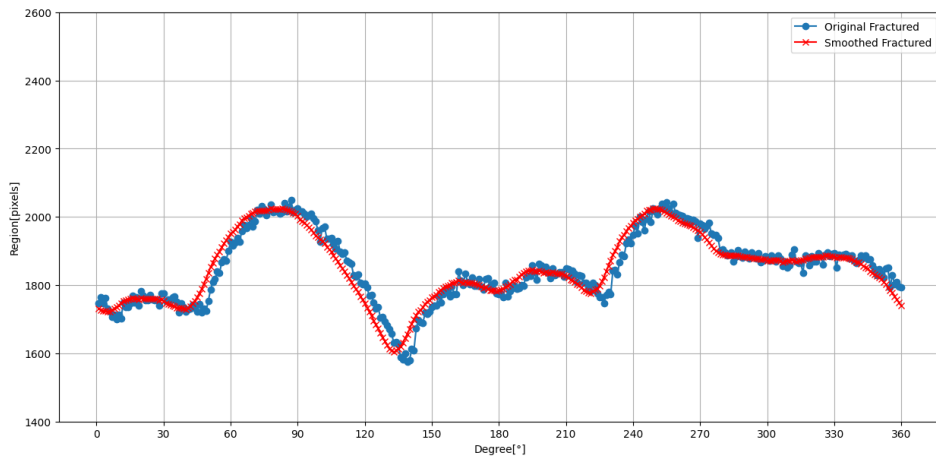


Figure 29 - Combined graph of the fractured tool, highlighting deviations indicative of a fracture.

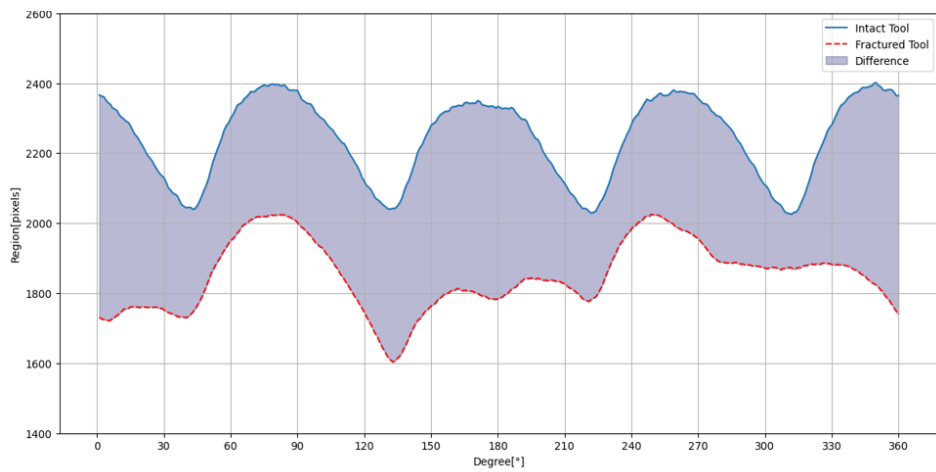


Figure 30 - Differential graph obtained by subtracting the smoothed intact tool graph from the smoothed fractured tool graph, emphasizing areas discrepancy.

The analysis leverages changes in the graphical patterns, which disrupt the periodic nature of the intact tool's profile, as indicators of damage. For instance, a single edge fracture, evident between  $130^\circ$  and  $220^\circ$ , might not significantly alter the total area difference between an intact and a fractured tool. However, it disrupts the consistency of the tool's profile, thus revealing potential issues. This nuanced approach enhances the sensitivity of fracture detection, allowing for the identification of smaller fractures. These fractures may not result in large area differences but are crucial for maintaining tool integrity and performance.

Identifying fractures with this level of precision enables targeted maintenance actions, potentially reducing downtime and extending tool life by facilitating timely interventions. The ability to detect subtle changes in the tool's profile, even when the changes do not result in a significant difference in the calculated area, highlights the diagnostic capability of this system to preemptively manage tool condition effectively.

### **4.3. Future Directions**

The current methodology calibrates the camera using the tool's width at the bottom as a reference for determining a single pixel's area. However, this approach does not fully account for the camera's perspective, which can cause discrepancies in pixel representation due to perspective distortion. Specifically, a set distance at the top of the tool may be represented by a different number of pixels than the same distance at the bottom. To address this issue, future enhancements could utilize the constant width of the tool along its height as a calibration reference. This would enable the system to more accurately compensate for the camera's perspective, ensuring consistent pixel representation across different parts of the tool.

Moreover, the integration of machine learning algorithms offers a promising path for automating condition assessments and improving diagnostic precision. Machine learning could analyze patterns within the graphical data generated during tool condition monitoring, facilitating the automatic detection of fractures and potentially predicting tool wear before it becomes critical. Such integration aligns with the objectives of smart manufacturing and Industry 4.0, highlighting the evolution of diagnostic tools to support more proactive and predictive maintenance strategies.

The incorporation of advanced cameras could further refine the system's diagnostic capabilities, enhancing the resolution and clarity of images used for analysis. This

improvement would be particularly beneficial for identifying subtle signs of wear or damage that current hardware may not detect.

Additionally, the application of coolants during machining processes could possibly obscure the tool's images, potentially complicating diagnostic efforts. Fortunately, most CNC milling machines are equipped with air blow devices. To mitigate the issue of coolant interference during tool condition assessments, it is recommended that these air blow systems be activated before tool changes and video capture begin. This proactive use ensures the tool remains clear of droplets, maintaining the visibility needed for accurate diagnostic imaging.

## 5. SUMMARY

### 5.1. Conclusion

This study has demonstrated the development and validation of a camera-based tool condition monitoring (TCM) system for CNC machining, achieving several key milestones:

- Developed a novel, image processing-based TCM system that utilizes consumer-grade cameras for monitoring.
- Enabled real-time detection of tool breakage and near real-time identification of edge fractures using accessible image processing techniques such as frame extraction, background subtraction, thresholding, and morphological operations.
- Showcased the system's use with standard camera phones for high-resolution video recordings, enhancing the accessibility and cost-effectiveness of advanced monitoring technologies in manufacturing.
- Introduced a scalable solution that integrates advanced diagnostic capabilities into manufacturing environments without requiring significant investment in specialized equipment.

### 5.2. Suggesting Further Exploration Options

Furthermore, this research opens avenues for future exploration, particularly in the realms of:

- Enhancing diagnostic accuracy using higher quality imaging equipment
- Automating condition assessment with the integration of machine learning algorithms, including more sophisticated automated thresholding to further improve precision.

By addressing a previously under explored area of direct monitoring methods through image processing, this work contributes significantly to the field of advanced manufacturing maintenance. It lays the groundwork for more proactive, predictive, and preventative maintenance strategies, aligning with the evolving needs of modern manufacturing environments.

Szombathely, 2024 April

Alireza Falah

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## 7. SHORT SUMMARY

This research introduces a simple yet novel and effective approach for tool condition monitoring (TCM) in CNC machining through the application of image processing techniques. Utilizing a consumer-grade camera capable of recording videos at 60 frames per second, the study demonstrates a cost-effective method for detecting tool breakage and identifying edge fractures. Basic image processing techniques, including frame extraction, background subtraction, thresholding, and morphological operations, are applied to analyze the captured images and videos.

The proposed system addresses the limitations of traditional TCM methods by providing real-time, accurate monitoring without the need for expensive and specialized equipment. This research not only offers a practical solution to enhance the efficiency and accuracy of CNC machine operations but also aligns with advancements in smart manufacturing and Industry 4.0. By integrating readily available technology, the approach makes advanced TCM accessible to a broader range of manufacturing environments.

Moreover, this study paves the way for future research in this area, suggesting potential for further refinement and broader application of such monitoring techniques. Future directions could include the incorporation of machine learning algorithms to automate the analysis process, improvements in camera technology for higher resolution imaging, and the development of more sophisticated image processing algorithms to handle a wider variety of tool conditions and machining scenarios. This research underscores the importance of innovative, accessible solutions in advancing the capabilities and efficiency of modern manufacturing systems.

**Keywords:** *CNC Tool Monitoring, Image Processing, Smart Manufacturing*