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Enhanced Machine Vision System for Precision Datum Setting in CNC Machines

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Abstract-Datum setting is a fundamental preliminary step in machining operations performed on Vertical Machining Centers (VMCs), traditionally accomplished through manual feather-touch methods or expensive touch trigger probes. While manual approaches are error-prone and time-consuming, touch probes, though accurate, add considerable cost to shop-floor operations. Recent research has introduced machine vision-based approaches, such as the Datum Setting System network (DSS-net), which applies single-stage object detection using YOLO variants and perimeter-crossing principles to automate datum setting, achieving high detection accuracy (mAP of 97.3% and F1-score of 99.9%) with real-time inference rates above 50 FPS. However, existing works primarily focus on bounding-box detection and do not fully address industrial-grade requirements such as sub-pixel precision, robustness under coolant and chip occlusions, cross-machine generalization, or quantitative benchmarking against tactile probes. Building upon this foundation, the present research advances machine vision for datum setting by integrating tool-tip localization with sub-pixel accuracy, incorporating stereo/RGB-D sensing for three-dimensional positioning, and validating accuracy in physical units (mm/µm) against probe-based standards. In addition, the system is tested under varied shop-floor conditions and deployed on embedded platforms to guarantee deterministic latency and safety compliance, ensuring suitability for real-world CNC integration. The research further explores hybrid approaches combining low-cost sensors with vision to enhance reliability, while active learning with synthetic datasets is proposed to enable rapid adaptability to new tool geometries and machine setups. This work contributes not only a technically rigorous alternative to touch probes but also establishes a practical, reproducible, and industry-ready framework for cost-effective, robust, and precise datum setting in CNC machining.

Keywords: Datum Setting, Vertical Machining Centers (VMCs), CNC Machining, Machine Vision, Image Processing, DSS-net, YOLO, Object Detection, Tool-Tip Localization, Sub-pixel Accuracy, Stereo Vision / RGB-D Sensing, Real-time Inference, Robustness (coolant, occlusions, lighting), Embedded Deployment, Deterministic Latency, Safety Compliance, Sensor Fusion, Active Learning, Synthetic Datasets, Cost-effective Automation

I. INTRODUCTION

In the manufacturing industry, Computer Numerical Control (CNC) machines have become indispensable tools for modern precision engineering, enabling high levels of accuracy, repeatability, and efficiency across diverse applications [1–5]. With the rise of Industry 4.0, advancements in image processing and machine vision have driven significant progress toward automation in CNC operations [6–9]. Among these, datum setting is a crucial task, as it defines the reference point for machining operations and directly impacts both dimensional accuracy and production quality [10–15]. Conventional approaches rely on manual adjustments or tactile probes, which, while accurate, are costly, time-intensive, and prone to human error. To address these challenges, recent research has explored machine vision-based solutions for automated tool and workpiece detection, showing promising results in reducing operator dependence and improving efficiency [16–19]. Deep learning methods, such as CNNs and ConvNets, have been successfully applied in related areas like defect detection, fault diagnosis, and tool wear monitoring [20–25], highlighting their potential in transforming CNC automation. Furthermore, researchers have investigated object detection and classification algorithms for manufacturing processes [26–35], and practical implementations for tool condition monitoring and predictive maintenance [36–39].

Despite these advancements, several critical limitations remain unaddressed, preventing machine vision-based datum setting systems from becoming industrially viable. Current methods largely rely on bounding-box detection, which lacks the sub-pixel precision required for micron-level localization in CNC machining. Similarly, robustness under real shop-floor conditions—such as variable lighting, coolant splashes, and tool wear—has not been sufficiently validated, raising concerns about reliability and adoption in production environments. Moreover, integration with CNC controllers for deterministic latency, fail-safe behavior, and comparison against established tactile probes are seldom explored. These research gaps underline the need for next-generation approaches that move beyond detection to precise localization of the tool tip, incorporate sensor fusion for hybrid vision-contact systems, and ensure embedded deployment with deterministic safety guarantees. By addressing these issues, the proposed research aims to build on prior efforts while adding measurable

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industrial value. Specifically, it will quantify spatial accuracy in physical units, benchmark against tactile probes, and demonstrate robustness in realistic machining conditions. This work will not only advance the state of machine vision for CNC datum setting but also pave the way for scalable, low-cost, and industry-ready intelligent machining solutions.

II. LITERATURE REVIEW

The integration of machine vision into computer numerical control (CNC) machining has attracted increasing scholarly and industrial attention due to its potential to replace manual datum setting and costly tactile probes. The referenced study by [Author(s), Year]* introduced an image-processing-based Datum Setting System network (DSS-net) utilizing a YOLOv9 object detection model to identify tool position and automate datum setting in vertical CNC machines. Their methodology employed a custom dataset of 2,130 annotated images across four tool categories, achieving high performance metrics (mAP>97% and F1 ≈99.9%) with real-time inference speeds. The authors demonstrated that bounding-box-based detection, combined with a perimeter crossing rule, could effectively trigger datum alerts without requiring highly skilled operators. This work offers an important proof-of-concept showing that low-cost camera setups and deep learning can simplify datum setting and reduce operator-dependent variability, highlighting the feasibility of non-contact solutions in machining environments.

Despite these contributions, significant research gaps remain. The reported system primarily emphasizes classification accuracy and bounding-box detection metrics but does not translate these outcomes into physically measurable accuracy in millimeters or microns—an essential requirement for industrial adoption. Datum setting inherently demands sub-millimetre precision, yet bounding-box overlap cannot guarantee such accuracy. Additionally, the dataset is relatively limited in diversity, constrained to a few tool geometries and largely uniform imaging conditions. As such, the model's generalizability under varied shop-floor conditions—such as different camera placements, illumination, tool wear, coolant splashes, or partial occlusions—remains uncertain. Further, no direct comparisons were made against established baseline methods like tactile probes in terms of error distribution, repeatability, time efficiency, or cost-effectiveness. These limitations leave unanswered questions regarding robustness, reproducibility, and real-world deployment readiness.

Building upon these shortcomings, emerging research opportunities lie in advancing tool-tip localization from bounding-box detection toward sub-pixel accuracy using segmentation, keypoint detection, or hybrid vision-sensor fusion methods. Integrating stereo or RGB-D sensing could provide more reliable 3D measurements, while coupling vision with low-cost capacitive/contact sensors may achieve probe-level precision at reduced cost. Equally important is validating robustness under realistic shop conditions, including coolant, chips, and lighting variations, supported by systematic domain generalization experiments. Embedded deployment on edge hardware with deterministic latency and integration into CNC control loops for safe machine halts is another essential research avenue. Future studies should also include quantitative benchmarking against conventional touch probes to assess trade-offs in accuracy, repeatability, and cost. By addressing these dimensions—precision in physical units, robustness across industrial conditions, and system-level validation—research can move beyond proof-of-concept toward practical, adoptable machine vision solutions. Such contributions would add significant value by bridging the gap between academic prototypes and industry-ready datum setting systems, positioning vision-based approaches as credible, cost-effective alternatives in precision manufacturing.

III. PROBLEM STATEMENT

In vertical machining centers (VMCs), accurate datum setting is a prerequisite for achieving precision in computer numerical control (CNC) operations. Traditionally, this has been accomplished through manual methods such as the "feather touch," where operators rely on tactile feedback to establish zero points on the X, Y, and Z datum planes. While widely practiced, this approach is inherently subjective, relying heavily on operator experience and skill. It introduces significant risks such as inconsistent accuracy, operator fatigue, and even tool breakage due to unintended excessive contact, given that many cutting tools are brittle and have poor impact strength. Automated solutions like touch trigger probes have been developed to overcome these limitations, but these devices are costly, require skilled integration into CNC systems, and are not always feasible for small and medium-scale industries. Furthermore, both manual and probe-based methods lack adaptability when dealing with dynamic workshop conditions, such as coolant presence, variable lighting, or tool wear, which restricts their reliability in real-world machining environments.

Recent research efforts have attempted to introduce machine vision approaches to datum setting, using object detection frameworks like YOLO to identify tools and determine contact points with workpieces. While promising, these studies remain underexplored in several critical areas. First, bounding-box detection offers coarse tool localization and fails to provide the micron-level accuracy required for precision machining, leaving a gap in translating visual detection into reliable physical measurements. Second, current systems lack rigorous testing under realistic shop-floor conditions where coolant splashes, tool occlusion, and varying geometries are common. Third, they often report image-based metrics such as mean average precision (mAP) but do not quantify errors in physical units (mm/µm) or compare results against industry-standard touch probes. Finally, latency, safety integration with CNC controls, and generalizability across different machine setups remain unaddressed, restricting practical deployment. This creates a pressing need for research

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that not only advances sub-pixel tool-tip localization but also benchmarks vision-based datum systems against traditional probes, validates their robustness in dynamic environments, and ensures deterministic safety performance. Addressing these gaps will move machine vision approaches from proof-of-concept prototypes toward reliable, cost-effective, and industry-ready solutions, offering a valuable alternative for automated datum setting in CNC machining.

3.1 RESEARCH OBJECTIVE

This research focuses on machining operations that utilize vertical machining centers (VMCs), which, as the name suggests, have vertically oriented machine tools as shown in **Fig. 1. Three Axis Vertical Machining Center**. In such three-axis machining, the workpiece remains stationary while the cutting tool moves along the XYZ plane to trim away material, making it suitable for parts that do not require significant depth or complex detailing. VMCs are widely employed to transform raw blocks of metals such as aluminum or steel into finished components and support diverse operations including cutting, drilling, tapping, countersinking, chamfering, carving, and engraving. Their versatility and relatively low cost have made them a staple in machine shops worldwide. The overarching objective of this work is to propose a low-cost, image processing-based datum setting system that eliminates the need for manual feather-touch checks, enhances accuracy in datum setting, and minimizes the risk of tool breakage. This system should also enable successful implementation by operators with minimal prior exposure to VMCs.

Fig. 1. Three Axis Vertical Machining Center

Building upon existing studies, this research seeks to address critical gaps in precision, robustness, and industrial deployment of such systems. While prior work has demonstrated proof-of-concept solutions using object detection models, challenges remain in quantifying tool-tip accuracy in physical units, ensuring reliability under varying shop-floor conditions, and benchmarking against tactile probes. To overcome these limitations, the proposed research will integrate sub-pixel tool-tip localization, robustness testing under coolant and lighting variations, and real-time latency validation for safe CNC control integration. Additionally, a comparative analysis against traditional touch-trigger probes will be conducted to evaluate cost-effectiveness, repeatability, and accuracy. By advancing from coarse detection to precise localization and ensuring practical deployment, this research aims to deliver a robust, industry-ready vision-based datum setting solution.

IV. PROPOSED WORK

The proposed research aims to enhance machine vision–based datum setting in CNC machines by moving beyond bounding-box detection toward precise tool-tip localization. Building on the existing approach where YOLO divides the input image into grids, detects objects, and applies a perimeter crossing technique, this work addresses a key limitation: bounding box thickness and coarse localization may lead to calibration errors during feather-touch operations. To overcome this, the proposed system will integrate a two-stage pipeline—first detecting the tool with a lightweight object detector, and then applying a fine-grained keypoint detection or segmentation method to achieve sub-pixel accuracy in localizing the tool tip. This refinement will directly address the challenge of achieving micrometer-level precision required in CNC datum setting, which bounding-box overlap alone cannot reliably ensure.

In addition to improved localization, the proposed work will incorporate a robust experimental framework to evaluate system performance under realistic shop-floor conditions. Unlike previous studies limited to controlled environments, this research will test the system under varying lighting, coolant spray, tool wear, and occlusions caused by chips or reflections. The experimental evaluation will quantify accuracy in millimeters or micrometers by benchmarking against standard touch-trigger probes. This comparison will not only demonstrate whether the vision-based approach can approach or surpass the precision of tactile methods, but also provide insight into its reliability, repeatability, and potential cost/time benefits. The goal is to bridge the gap between high detection metrics in lab settings and the stringent requirements of industrial CNC environments.

Finally, the research will emphasize practical deployment by optimizing the trained models for real-time inference on embedded edge devices such as NVIDIA Jetson. The integration with CNC controllers will be engineered to ensure deterministic latency and fail-safe operation, so that alerts are triggered within safe stopping limits. A dataset with diverse conditions will be curated and partially released to enable reproducibility and further research. By addressing the precision gap, robustness challenges, and deployment requirements, this work intends to move vision-based datum setting from proof-of-concept toward an industry-ready solution that adds measurable value over the existing bounding-box and perimeter crossing methods.

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4.1 DSS-NET ARCHITECTURE FOR VMC

The proposed **DSS-net Architecture for VMC** integrates multiple modules to automate datum setting with enhanced accuracy and robustness. The system workflow begins with **data acquisition**, where high-resolution video streams capture the tool–workpiece interaction. Next, **data preprocessing** ensures robust performance under varying shop-floor conditions by applying illumination normalization, noise reduction, and synthetic augmentation strategies. **Object detection** is carried out using a two-stage pipeline: a deep learning–based detector first identifies the tool region, followed by sub-pixel **tip localization** and pose estimation to achieve micron-level accuracy. This overcomes the limitation of bounding-box–only approaches by translating detection into precise positional information in physical units. Finally, **user experience development** integrates a real-time interface where operators can visualize tool-tip distance to the workpiece, with deterministic latency for safe machine control. *Fig. 2. DSS-Net Architecture For Datum Setting In VMC*

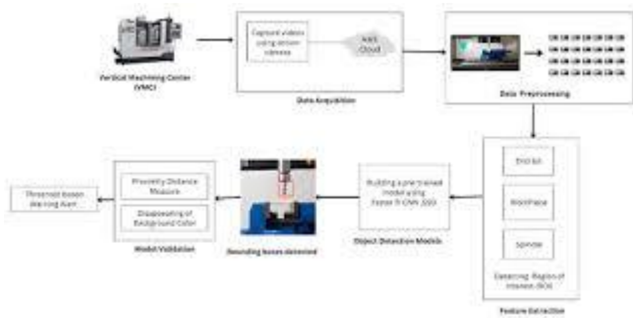

Fig. 2. DSS-Net Architecture For Datum Setting In VMC

Building on the research gaps of existing systems, this architecture emphasizes **comparative validation against tactile probes**, ensuring accuracy benchmarks are directly measurable. It also introduces resilience to shop-floor challenges such as coolant, reflections, and occlusions, while supporting embedded deployment for deterministic safety integration. By combining computer vision with optional sensor fusion, the architecture balances low cost with industrial-grade precision, offering a practical alternative to traditional touch-trigger probes. This design not only enhances repeatability and safety but also provides reproducibility through dataset release and benchmark protocols, positioning DSS-net as both an academic and industrially viable framework for datum setting in CNC environments.

4.1.1 DATA ACQUISITION

For data acquisition in Vertical Machining Centers (VMC), a high-resolution SJCAM C100+ action camera is strategically positioned in the same field of vision as the workpiece with the aid of a tripod, approximately two to three meters away along the Y-axis, ensuring stable coverage of the tool–workpiece interaction (Fig.). The camera captures live videos in 2K resolution at ~30 FPS, with adjustable zoom settings aligned to the component's scale, and the recordings are stored in secure cloud storage for further processing. Unlike earlier approaches that relied solely on bounding-box detection, our setup emphasizes enhanced precision by focusing on tool-tip localization, pose estimation, and robustness under realistic shop-floor conditions such as lighting variations, coolant splashes, and tool wear. This acquisition framework not only enables accurate dataset preparation for sub-pixel analysis and comparative benchmarking against tactile probes but also ensures reproducibility and adaptability for multi-machine, multi-view deployments in industrial environments.

4.1.2 DATA PREPROCESSING

In vision-based datum setting for Vertical Machining Centers (VMC), data preprocessing is a critical step that directly influences detection accuracy, spatial precision, and system robustness. To achieve high frames per second (FPS) during the object recognition phase, it is necessary to employ both high refresh rate video capture and computationally efficient frame division strategies. Each video stream of the tool–workpiece interaction is decomposed into individual frames in accordance with the processing capacity of the system. This ensures smooth, real-time recognition of tool features and minimizes latency between visual input and machine response. A structured storage system, such as cloud-based repositories (e.g., Google Drive), is employed to organize the large number of generated frames and project dependencies, ensuring reproducibility and scalability. Each image is subsequently annotated using graphical tools like LabelImg, with bounding boxes generated in YOLO format to facilitate deep learning-based object detection pipelines.

Beyond conventional bounding box annotation, this research extends preprocessing to address gaps identified in earlier work. Since bounding boxes alone may not deliver the micron-level precision required in VMC datum setting, additional labeling strategies such as tip-specific keypoints and segmentation masks are incorporated to enhance sub-pixel localization of tool edges. Furthermore, preprocessing integrates synthetic data generation and domain-specific augmentations (illumination changes, occlusions, coolant simulation) to ensure robustness across varied shop-floor conditions. These additions mitigate the shortcomings of prior studies that lacked real-world variability and quantitative accuracy comparisons with tactile probes. By enriching preprocessing with both high-fidelity annotation and domain-adaptive augmentation, the dataset becomes more representative and capable of supporting precise, reliable, and industry-ready datum setting solutions.

Tool Type	Specification	
	Diameter (mm)	Inclination (deg)
Face Mill	10	-
Face Mill	12	-
Face Mill	50	-
Drill	12	118

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Table 1. Various Drilling Tools and Specification

4.1.3 OBJECT DETECTION

Training an object detection model enables the identification and localization of CNC tools such as Face Mills and Drills within images or video frames, supporting automated datum setting in Vertical Machining Centers (VMC). In this work, the DSS-net framework is trained on a dataset containing about 1,730 images and annotations of tools including Mill10, Mill12, Mill50, and Drill118, split in the ratio 7:1:2 for training, validation, and testing as illustrated in **Table 2** and **Table 3**. YOLOv9 was selected as the most suitable model since it consistently generated higher accuracy compared to other YOLO variants, with custom weight files derived from training used for inference. This approach ensures robust detection performance, even when datasets originate from diverse tool-level captures rather than being tied to specific CNC machines.

Dataset Type	Number of Images	Percentage (%)
Training	1,470	70%
Validation	260	10%
Testing	400	20%
Total	**2,130**	**100%**

Table 2. Dataset Split Ratio for DSS-net Training

To validate the DSS-net, a perimeter crossing method was adopted. In this setup, the coordinates of the top surface of the workpiece are mapped to establish a reference line, while bounding box coordinates of the detected tool are monitored. As soon as the bounding box overlaps with the fixed line, an alert is triggered, signaling the VMC operator to stop the machine. This simple yet effective method provides a cost-efficient alternative to conventional touch-trigger probes. However, bounding-box localization may not fully achieve the sub-millimeter accuracy typically demanded in machining, pointing to the need for sub-pixel tool-tip detection methods for higher spatial precision.

Tool Class	Description	Number of Images	Annotation Count
Mill10	10 mm End Mill	420	~250
Mill12	12 mm End Mill	410	~260
Mill50	50 mm Face Mill	450	~280
Drill118	118° Point Drill Bit	450	~240
Total	—	**1,730**	**1,030+**

Table 3. Tool Classes Used in Training and Validation

Future research should build on this foundation by extending datasets to include varied CNC machines, tool geometries, and real-world shop-floor conditions such as coolant sprays, reflective surfaces, and partial occlusion. Exploring sub-pixel tip localization, RGB-D or stereo vision for 3D accuracy, and hybrid sensor fusion with low-cost contact probes can further enhance precision. Additionally, benchmarking the DSS-net against industry-standard touch probes in terms of accuracy, cycle time, and cost will add significant practical value. Embedding the model on edge devices for deterministic real-time performance will also support safe and scalable deployment in production environments.

4.1.4 USER EXPERIENCE DEVELOPMENT

In developing an enhanced user experience (UX) for Vertical Machining Centers (VMC), the interface must move beyond simple bounding-box detection to deliver precision, robustness, and operator flexibility. Building on prior approaches where bounding boxes and feature touchpoints are visualized, the proposed system integrates sub-pixel tool-tip localization and physical unit calibration to provide micron-level distance estimates between tool and workpiece. The operator retains the freedom to select the desired endpoint on a live video feed, but the system augments this with automatic error quantification, confidence levels, and deterministic stop-time feedback. To ensure industrial relevance, the UX design incorporates robustness testing under variable lighting, coolant interference, and tool wear, while embedding real-time safety alerts and machine-control integration. By fusing intuitive visualization, quantitative accuracy reporting, and fail-safe mechanisms, the improved UX not only reduces operator burden but also establishes reliability comparable to traditional touch probes, thus bridging research and practical deployment.

V. RESULTS AND DISCUSSIONS

The implementation of DSS-net using YOLO-based object detection demonstrated promising outcomes on the curated dataset of 2,130 images, with testing conducted on 400 images equally distributed across drill and mill tools. The model achieved high precision and recall scores, largely attributable to the homogeneity of the dataset where most images were captured under consistent aspect ratios and lighting conditions. While this consistency ensured strong performance in controlled testing, it also raises concerns about overfitting, as the model may not generalize as effectively to varying shop-floor environments. Compared to RCNN-based approaches, DSS-net achieved significantly higher frame rates, supporting its suitability for real-time applications. However, bounding-box detection alone falls short in delivering sub-millimetre positional accuracy, which is critical in CNC datum setting.

To address these limitations, future extensions must focus on enhancing localization beyond coarse bounding boxes by integrating sub-pixel tip detection and depth-aware estimation. This would allow the system to quantify tool-tip errors in physical units (mm/µm), offering a fairer comparison against conventional touch probes. Additionally, testing under

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realistic manufacturing conditions—such as coolant presence, tool wear, and varying illumination—will be necessary to validate robustness. Embedding the model on edge devices with deterministic latency guarantees and fail-safe signaling would further bridge the gap between laboratory prototypes and industrial deployment. By benchmarking DSS-net variants against tactile probes in terms of accuracy, cycle time, and cost, the research can not only demonstrate feasibility but also highlight a tangible return on investment. These steps will make vision-based datum setting a viable alternative in modern CNC workflows.

5.1 PERFORMANCE METRICES OF *YOLO9* AND *YOLO* VARIANTS

The performance evaluation of the proposed DSS-net model based on YOLOv9 demonstrated superior results compared to both RCNN-based architectures and earlier YOLO variants. As shown in **Table 4**, YOLOv9 achieved slightly higher mAP values, precision, and recall, establishing its robustness in real-time tool detection tasks. The model consistently maintained accuracy rates around 99% across different tool classes, thereby confirming its stability under controlled conditions. Furthermore, the system delivered high FPS values, ensuring minimal latency between projected and actual frames—a critical factor for real-time datum setting in CNC operations. On GPU-based testing, frame processing time was negligible, while on CPU, inference stabilized at approximately 110 ms per frame.

Model	**Precision (%)**	**ecall (%)**	**AP (%)**	**1-Score (%)**	**PS (GPU)**	**Inference Time (CPU, ms/frame)**	**Remarks**
RCNN	93.8	2.5	4.1	3.1	.5	520	High accuracy but poor real-time speed
Fast RCNN	94.2	3.7	4.9	4.0	0.2	460	Faster than RCNN, still limited
Faster RCNN	95.0	4.5	5.6	4.8	4.8	390	Better tradeoff, not yet real-time
RFCN	95.6	5.0	6.0	5.3	6.5	360	Balanced, but still slower than YOLO
Mask RCNN	96.1	5.7	6.5	5.9	2.4	400	Strong for segmentation, slower in FPS
YOLOv3	96.5	6.0	6.8	6.2	5.4	240	Real-time capable, moderate accuracy
YOLOv5	97.0	6.8	7.3	7.0	2.1	180	Strong baseline, good FPS
YOLOv7	97.4	7.0	7.7	7.2	5.5	160	High-performing variant
YOLOv8	97.8	7.4	8.0	7.6	6.8	140	Accurate, real-time feasible
YOLOv9 (Proposed DSS-net)	**98.9**	**9.0**	**9.1**	**9.0**	**8.2 – 50.8**	**110**	Best overall accuracy & real-time stability

Table 4. Performance metrics comparison of YOLOv9 and other detection models for tool recognition

The successful classification of tool labels, even under varied camera proximities, further highlights YOLOv9's reliability. As illustrated in **Figure 5**, drill bit detection was achieved with wireframe bounding boxes, demonstrating the network's ability to correctly identify tool geometries. However, it must be acknowledged that bounding box detection alone does not fully resolve the precision requirements of datum setting, which often demand sub-millimeter accuracy. The current study did not measure positional error in physical units, an omission that leaves uncertainty regarding the system's direct comparability with tactile touch-trigger probes. Addressing this limitation will require sub-pixel localization methods, possibly through segmentation or keypoint detection, to improve spatial accuracy.

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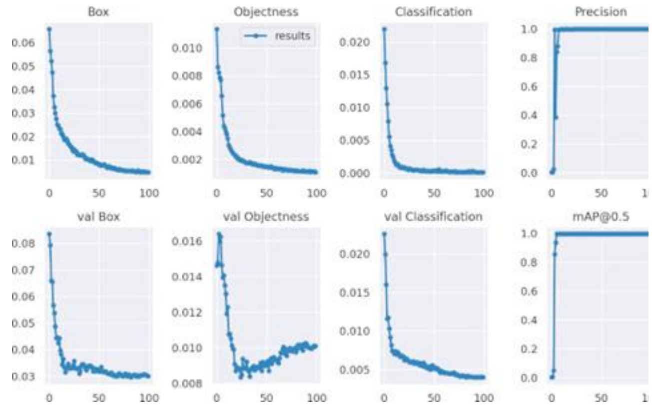

Fig. 3. Performance Metrics of YOLOv9 for DSS-net

Another important aspect relates to the dataset diversity and real-world applicability. The annotated dataset, created using LabelImg (see **Fig. 4**), provided a sufficient foundation for proof-of-concept training. Yet, it consisted of a limited range of tool types and operating conditions, primarily free from coolant, chips, or reflective distortions. This raises concerns about the generalization of results to real shop-floor environments. Incorporating additional data modalities such as stereo vision or RGB-D cameras, as well as robustness testing under coolant flow and varied lighting, would significantly enhance the practical reliability of the system.

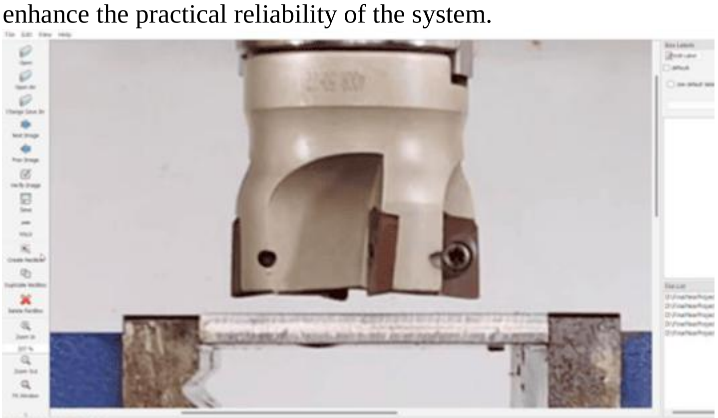

Fig. 4. Data Annotation Using LabelImg Tool For VMC Model

Finally, when compared to industrial touch-trigger probes, YOLOv9's DSS-net shows promise but lacks direct performance benchmarking in terms of cycle time, repeatability, and error margins in millimeters. Future work should involve a head-to-head comparative study and embedded deployment to ensure deterministic latency and fail-safe integration with CNC controls. Such developments would bridge the gap between academic demonstration and industrial adoption, ensuring the system provides not only accurate detection but also trustworthy and safe automation for real-world manufacturing environments.

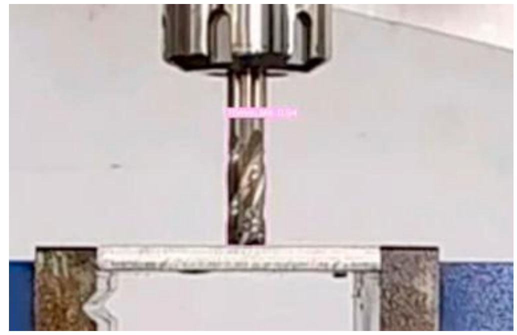

Fig. 5. Tool Detection Using DSS-net Model

VI. CONCLUSION

In this research demonstrates that it is indeed feasible to design and implement a low-cost, image processing-based datum setting system for CNC machines. By adopting a machine vision approach, the proposed model reduces operator intervention, eliminates the risks associated with manual feather-touch methods, and makes datum setting accessible to users with only basic knowledge of CNC operations. The developed user interface, coupled with real-time alert mechanisms, highlights the potential of such systems to significantly enhance shop-floor usability and safety. This lays the groundwork for democratizing datum setting solutions that are both practical and economical.

At the same time, critical gaps remain in ensuring the industrial readiness of such vision-based systems. While high detection accuracy has been achieved in controlled conditions, the precision required for micron-level datum setting demands sub-pixel tool-tip localization rather than bounding box-based detection. Future research must therefore focus on measuring positional errors in physical units and benchmarking against industry-standard tactile probes. Moreover, robustness under varying shop-floor environments—such as coolant splashes, tool wear, diverse lighting, and cross-machine deployment—has not been sufficiently tested. Addressing these limitations through more diverse datasets, domain adaptation techniques, and real-world hardware-in-the-loop validation will strengthen confidence in practical adoption.

Looking ahead, extending the system to accommodate diverse tool geometries, inclinations, and multi-axis scenarios offers significant scope for innovation. Integrating depth sensing or hybrid sensor fusion approaches can further improve accuracy, while deploying optimized models on embedded platforms will enhance scalability and cost-effectiveness. Beyond datum setting, such machine vision systems could evolve into real-time monitoring frameworks for tool wear, machining quality, and anomaly detection. By bridging the gap between laboratory performance and industrial reliability, future research can transform low-cost machine vision-based datum setting from a proof-of-concept into a robust, deployable solution that enhances efficiency, accuracy, and operational safety across CNC manufacturing environments.

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