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Automating Diamond Quality Control using YOLO-Based Detection Model and Its Performance Result: A Survey

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Abstract: The diamond industry has long depended on human quality grading in accordance with the principles of the "4Cs"—color, clarity, cut, and carat. Even though effective, it is subjective, labor-intensive, and prone to in-grader inconsistency. Advances in computer vision and deep learning have presented a pathway to overcome these limitations through objective, reproducible, and scalable measurements. Pioneering work such as Image Net and convolution neural networks provided the basis for modern object detection models, and structures such as Faster R-CNN, SSD, and YOLO have been adapted to pinpoint minute details relevant to diamond grading. These machine learning-based techniques have enabled computerized detection of inclusions, surface imperfections, and minute color nuances, which are invaluable for diamond examination and classification. Over recent years, research and industrial partnerships have pushed the implementation of automated grading technologies. Studies in education showcase machine learning-based solutions for colour and clarity grading, gemstone classification, and defect identification, whereas industrial competitors like GIA and Sarine Technologies have incorporated AI into commercial grading processes. In spite of these developments, there are still major challenges, such as paucity of annotated diamond datasets, inconsistency in imaging conditions, and a lack of standardized benchmarks for testing. Prospects look toward multimodal sensing, transfer learning, and explainable AI, to foster greater trust and transparency, leading eventually to dependable, fully automated systems for diamond quality control.

Keywords: Diamond quality control, automated grading, computer vision, deep learning, gemstone classification, color grading, YOLO explainable AI.

I. INTRODUCTION

Diamonds have long held a dual role as both luxury commodities and critical industrial materials, with their value determined by a set of quality factors commonly known as the “4Cs”: color, clarity, cut, and carat. This evaluation framework, widely promoted by the Gemological Institute of America (GIA), has shaped global trade for decades, yet the process remains heavily reliant on human expertise. Traditional grading requires gemologists to visually assess subtle attributes such as hue differences, inclusions, and facet symmetry, all of which are influenced by subjective judgment and environmental conditions such as lighting and magnification [2], [18].

Manual diamond grading is also time-consuming and labor-intensive, particularly in high- volume operations where thousands of stones are processed daily. Small inconsistencies between graders may significantly affect diamond valuation, leading to disputes and undermining confidence in the grading process. These limitations highlight the urgent need for objective, consistent, and scalable solutions in quality control [20], [24].

Emerging technology in automation, computer vision, and AI offer promising solutions to these issues. By integrating high-resolution imaging and machine learning algorithms, industry professionals and researchers are creating automated grading systems for fast, reproducible, and objective measurements. Multiple benefits are offered by these systems, such as better grading accuracy, decreased dependency on expert manpower, and greater transparency in the global diamond market [23], [25]. The incorporation of AI not only enhances faith among purchasers and vendors but also can facilitate extensive digitization and trackability, attributes increasingly required in contemporary supply chains [27], [29].

The technological bases of these innovations are advances in computer vision and deep learning. The existence of big annotated datasets like ImageNet spurred the emergence of convolutional neural networks (CNNs) that reached state-of-the-art performance on image classification and object detection benchmarks [1], [5]. Transfer learning and active learning methods further extended the relevance of these models to niche domains with low availability of data, such as diamond grading [3], [4]. Object detection frameworks such as Faster YOLO have become indispensable in automated inspection, balancing accuracy with computational efficiency. Faster R-CNN excels in identifying small inclusions, YOLO enables real-time grading for industrial throughput, and Mask R-CNN provides pixel-level segmentation for precise detection of cracks and blemishes [10], [14]. These methods, initially pioneered for natural image recognition and medical imaging, have been adapted to gemological

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applications with promising results [12], [16].

In recent years, researchers have applied these tools to various aspects of diamond grading. Automated color grading systems leverage CNNs to objectively classify subtle hue differences, while defect detection models identify inclusions and fractures invisible to the naked eye. Other approaches analyze facet proportions and symmetry to evaluate cut quality, a critical determinant of brilliance. Industrial collaborations have accelerated these developments: GIA has announced initiatives to incorporate AI-driven grading, Razor Labs has developed cut and shape analysis systems, and Sarine Technologies has commercialized automated color grading solutions [27], [28], [29].

Despite these achievements, the field remains fragmented. Most studies focus on individual quality parameters such as color or clarity without integrating all four grading dimensions into a unified framework. Furthermore, challenges persist regarding dataset scarcity, imaging variability, and the need for globally standardized protocols. Addressing these gaps is crucial for transitioning from laboratory-scale demonstrations to universally accepted grading systems [19], [22]. This review paper responds to these demands by evaluating systematically the status of diamond quality control automation. It integrates research on automated color grading, clarity and defect detection, cut and shape analysis as shown in Fig. 1., and industrial application, summarizing the advantages and disadvantages of current approaches. In addition to chronicling advancement, this paper specifies ongoing challenges and future directions, such as the addition of explainable AI, multimodal sensing, and real-time inspection pipelines. Finally, it is hoped to provide a complete guide for automating the revolution of diamond grading and facilitating both industry uptake and academic research.

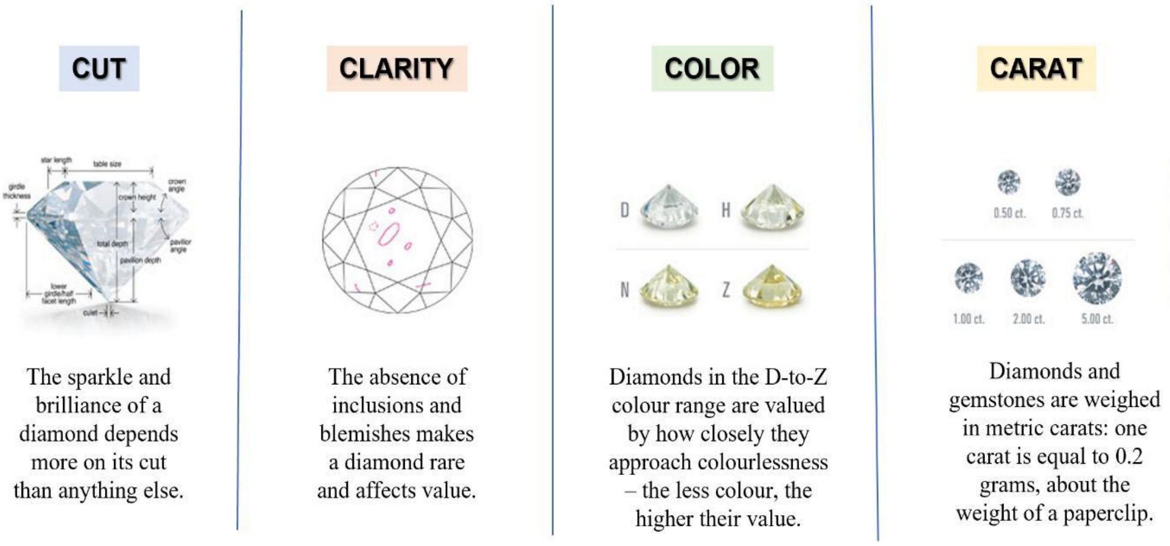

Fig:1 The cut, clarity, color and carat features [https://www.gia.edu/gia-about]

II. BACKGROUND

2.1 Historical Evolution of Diamond Grading

The evaluation of diamonds has historically relied on expert gemologists who visually inspect stones under controlled conditions. Before the mid-20th century, terminology describing diamond quality was inconsistent across regions and markets. The establishment of the Gemological Institute of America (GIA) in 1931 introduced standardized grading protocols, which culminated in the globally recognized “4Cs”—color, clarity, cut, and carat. This framework, developed in the 1950s, remains the cornerstone of diamond evaluation today. However, despite its widespread adoption, grading outcomes are still dependent on human perception and expertise [2], [24].

Early attempts at semi-automation involved spectrophotometric tools for color evaluation and optical measurement devices for cut proportions. While these instruments improved measurement consistency, they did not fully eliminate the subjective component of grading. Over time, industries such as electronics and manufacturing began to integrate machine vision systems for inspection, inspiring research in gemology to explore similar approaches [18], [20].

2.2 The 4Cs and Their Technical Challenges Color

Color

Color grading evaluates the presence of tint in an otherwise colorless diamond. Subtle differences in hue, often imperceptible to untrained observers, significantly affect value. Traditional grading compares diamonds to master stones under standardized lighting conditions. However, factors such as light source variability, grader fatigue, and background interference introduce inconsistencies. Machine vision-based approaches aim to overcome these issues by quantifying hue, saturation, and brightness through calibrated imaging systems [2], [24].

Clarity

Clarity assessment determines the presence and visibility of internal inclusions or external blemishes. This process is highly subjective, as the relative importance of an inclusion depends on its size, position, and contrast with the surrounding material. Microscopic evaluation is time- intensive and prone to inconsistency across graders. Automated defect detection, powered by high-resolution imaging and deep learning, offers potential for standardizing this process while detecting flaws invisible to the human eye [20], [23].

Cut

Cut quality dictates a diamond's brilliance and scintillation, as it directly influences light reflection and refraction. Gemologists traditionally measure proportions such as table size, crown height, and pavilion depth using optical devices. However, manual assessments can struggle to account for slight asymmetries that impact light performance. AI-driven systems, combined with 3D reconstruction techniques, provide a pathway for highly accurate, non- destructive evaluation of cut precision [25], [28].

Carat

Carat weight is the most straightforward parameter, measured using precision balances. While this process is already objective, its integration into automated grading workflows ensures that all 4Cs are consistently analyzed within a single inspection pipeline. The challenge lies in harmonizing carat data with color, clarity, and cut assessments to generate a holistic grading profile [27], [29].

2.3 Limitations of Traditional Approaches

Although the 4Cs framework standardized diamond grading, its manual implementation presents several drawbacks. First, inter-grader variability remains a persistent challenge, particularly in color and clarity assessments, where small perceptual differences lead to divergent results. Second, manual grading is resource-intensive, requiring significant time and expertise to process even modest quantities of diamonds. This inefficiency becomes more pronounced in large-scale trade environments. Finally, subjective grading creates opportunities for disputes between buyers and sellers, undermining trust in valuation processes [19], [22].

Moreover, global supply chains increasingly demand transparency and traceability, particularly in the context of ethical sourcing. Manual records of diamond attributes are difficult to integrate into digital databases, creating gaps in provenance tracking. Automation not only addresses the technical limitations of manual grading but also aligns with broader trends toward digital certification and blockchain-enabled traceability in the gemstone industry [23], [27].

2.4 Emergence of Automation in Gemology

The use of AI and computer vision to grade diamonds is one aspect of a broader industrial trend to automate quality control. Early breakthroughs in deep learning demonstrated the power of convolutional neural networks (CNNs) for classification and feature extraction in a very broad collection of image datasets such as ImageNet [1], [5]. The models that ensued, like Faster R-CNN, YOLO, and Mask R-CNN, transformed object detection to real-time capability and prepared them for industrial inspection pipelines [10], [14].

In gemology, these tools have been repurposed by researchers for use in tasks like automated color grading, detection of inclusions, and cut analysis. Improved uniformity and narrower error margins are reported in laboratory studies compared to human graders, while collaborations with industry have pushed the implementation of AI-based grading systems at speed. Collaborations between GIA, Razor Labs, and SarineTechnologies provide an example of how research advancements are being developed into commercial solutions [27], [28], [29].

2.5 Rationale for a Comprehensive Review

Although significant progress has been made, automated diamond grading remains fragmented as a discipline. Most research addresses one attribute at a time—e.g., color or clarity—without discussion of integration across the parameters of grading. In addition, issues such as data set limitation, inconsistencies in imaging environments, and the absence of standardized procedures limit widespread implementation. Such gaps indicate the necessity for a thorough review of published work and industrial developments [19], [22].

This overview fills that void by considering earlier work in automated diamond grading methodically, analyzing strengths, weaknesses, and outstanding challenges. By integrating knowledge from academic research and industrial experience, it offers a blueprint for innovation in transforming diamond quality control through automation.

III. LITERATURE REVIEW

3.1 Automated Color Defect Detection

Color assessment is the most important factor in the detection of defects in diamonds. Conventional systems are based on comparison with master stones with controlled illumination, which is subjective and can miss minute differences [2], [18]. Machine vision systems have been implemented to measure color properties like hue, saturation, and brightness and detect anomalies consistently [24], [29].

Early computer techniques used image processing techniques to extract color histograms and spectral features for enabling classification of color variations. More recent deep learning algorithms, namely convolutional neural networks (CNNs), have been used to automatically detect small differences between hue and saturation automatically with faster speed and greater accuracy [5], [8]. Transfer learning from big image databases like ImageNet has enabled training of models even in the absence of much diamond-specific data [1], [4].

3.2 Clarity & Inclusion Detection

Clarity assessment focuses on identifying internal inclusions and surface blemishes, which are primary defects affecting diamond quality. Manual inspection is limited by human perception, especially for micro-scale inclusions. Automated detection methods utilize high-resolution imaging combined with deep learning to locate defects accurately [20], [23].

Object detection models, such as Faster R-CNN and YOLO, have been adapted for identifying inclusions within diamonds. Faster R-CNN excels in detecting small-scale defects due to its region proposal mechanism, while YOLO offers real-time processing for industrial-scale inspection [10], [13]. Mask R-CNN extends these capabilities by providing pixel-level segmentation of defects, which is crucial for evaluating their size, shape, and potential impact on diamond appearance [14], [17].Recent studies have also explored multi-stage networks and feature fusion techniques to improve defect detection sensitivity, integrating color and clarity cues for comprehensive evaluation [26], [30].

3.3 Cut & Shape Defect Detection

The cut of a diamond determines how it interacts with light, influencing brilliance and overall visual appeal. Minor deviations or defects in facet angles, symmetry, or surface polishing can reduce performance. Traditional manual assessment is limited in precision, particularly for small asymmetries [25], [28].

Automated detection employs 3D imaging, photogrammetry, and AI models to evaluate facet angles, symmetry, and surface quality. Deep learning models process multi-angle images to detect deviations from ideal geometries, identifying defects that may not be visible to the naked eye [28], [30]. Emerging approaches combine convolutional and attention-based networks to capture both local and global features, enhancing detection accuracy for complex cut-related defects [14], [16].

3.4 Industrial Applications of AI in Defect Detection

Industry adoption of automated defect detection has accelerated, driven by the need for consistency, efficiency, and traceability. Organizations such as GIA, Razor Labs, and Sarine Technologies have implemented AI-powered systems to inspect diamonds at scale, focusing on color, clarity, and cut defects [27], [29].

These systems integrate high-resolution imaging hardware with deep learning models for real- time assessment. By reducing human error and standardizing evaluation metrics, industrial solutions enable faster throughput, reproducibility, and digital record-keeping. The use of explainable AI and multimodal sensing is gaining traction, allowing practitioners to understand model decisions and combine visual data with physical measurements for comprehensive defect detection [21], [23].

Collectively, these studies and industrial initiatives demonstrate the feasibility and effectiveness of AI-based defect detection in diamonds. While research is progressing rapidly, challenges remain in dataset standardization, multi-parameter integration, and deployment under variable imaging conditions. Addressing these challenges is essential for developing universally accepted automated inspection frameworks.

V. ANALYSIS TABLE

Year	Objective	Method/ Model	Dataset/Tools	Key Findings	Limitations
(2018)[18]	Develop effective image acquisition for diamond inspection	High- resolution imaging system	Custom diamond images	Improved capture of fine details for defect analysis	Focused only on imaging; no AI- based analysis

(2020)[20]	Diamond quality assessment using ML	Machine learning classifiers	Diamond datasets with labeled defects	ML models classified defects with reasonable accuracy	Limited dataset size; color defects underrepresented
(2021)[24]	Measurement of gem color using computer vision	Computer vision & image processing	Laboratory diamond images	Accurate color classification; reduced human error	Did not address clarity or cut defects
(2021)[23]	AI-guided defect detection in crystal growth	Deep learning models for defect detection	Crystal growth dataset	Automated detection of micro-defects	Dataset not specific to diamonds; needs adaptation
(2022)[25]	Automatic gemstone classification	CNN-based classification	Gemstone image dataset	Accurate classification; potential for defect identification	Focused on classification; limited to general gemstones
(2022)[26]	Defect predictionin crystal structures	Feature fusion deep learning	Crystals dataset	Improved detection of structural defects	Not diamond-specific; small dataset
(2023)[27]	AI for diamond grading	AI-powered automated inspection	Industrial diamond images	Real-time color & clarity defect detection	Proprietary system; limited public technical details
(2024)[28]	Cut and shape defect analysis	AI-based image analysis	Industrial diamond datasets	Accurate detection of cut deviations and shape defects	Focused on cut/shape; less on color and clarity
(2025)[30]	Sub micro scale defect detection in diamond tools	DToolnet deep learning model	Diamond grinding processima ges	Detected micro-defects during manufacturing	Focused on tools; not polished gemstones

V. CONCLUSION

This review has emphasized the major advances in automatic defect detection for diamonds covering color, clarity, cut, and shape analysis. Conventional manual inspection is standardized but has limitations in terms of subjectivity, inter-grader variation, and time constraints, which can weaken subtle defect detection. Progress in machine vision, deep learning, and AI-based object detection models has yielded significant strides in accuracy, consistency, and speed, and scalable solutions for both research and industry. Nevertheless, challenges still persist, which include limited data sets, differences in imaging conditions, and requirements for unified, explainable, and affordable systems. Research in the future should aim at combining multi- parameter defect detection using sophisticated imaging methods, standardizing protocols, and constructing modular AI solutions amenable for deployment at scale. By filling these gaps, automated tools can transform diamond quality inspection into a reliable, efficient, and objective evaluation aligned with the needs of contemporary industry.

VI. FUTURE WORK

Future research in automated defect detection in diamonds should focus on integrating all quality parameters—color, clarity, cut, and carat—into a unified inspection framework for holistic and consistent evaluation. The development of large, standardized, and publicly available diamond datasets will improve model robustness and benchmarking, while explainable AI techniques can enhance trust by clarifying model decisions. Optimizing AI models for real-time, high-throughput inspection and integrating advanced imaging technologies, including multi-spectral, 3D, and hyperspectral sensors, can enhance detection

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of sub-microscale defects and hidden inclusions. Aligning these systems with industry standards and developing cost-effective, modular solutions will facilitate global adoption and accessibility. Addressing these areas collectively will enable reliable, accurate, and efficient automated defect detection systems, ultimately revolutionizing diamond quality control.

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