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Real-Time Surface Defect Detection and Hardness Prediction in Metals using YOLOv8

1st RAJESHKUMAR S
Department of Computer Science
KPR Institute of Engineering and Technology
Coimbatore, India
suyamburajesh@gmail.com

2nd ARUL M
Department of Computer Science
KPR Institute of Engineering and Technology
Coimbatore, India
arulsriram2006@gmail.com

3rd HARINI M
Department of Computer Science
KPR Institute of Engineering and Technology
Coimbatore, India
harinimuthukumar0@gmail.com

4th ARUNKUMAR K R
Department of Computer Science
KPR Institute of Engineering and Technology
Coimbatore, India
arun8778jul@gmail.com

5th AKALYA S
Department of Computer Science
KPR Institute of Engineering and Technology
Coimbatore, India
akalyas0503@gmail.com

6th DHARASHREE S R
Department of Computer Science
KPR Institute of Engineering and Technology
Coimbatore, India
msrdharashree76@gmail.com

***Abstract*—Accurate calculation of surface quality and mechanical properties of metallic materials is vital in modern manufacturing. Old hardness testing includes destructive procedures that are overpriced and inefficient. This paper presents a computer vision-based framework for non-destructive surface hardness prediction using YOLOv8 for defect detection and a deep regression model for property estimation. The proposed system first recognizes flaws such as scratches, corrosion, and cracks on metallic surfaces, then extracts feature representations to predict the equivalent Vickers hardness value. Experiments conducted on a self-created dataset of steel and aluminum surfaces accomplished 94% mAP for defect classification and MAE <5% in hardness prediction. The results show that deep vision systems can allow real-time, non-contact material evaluation, linking the gap between computer vision and materials science.**

Keywords—Computer vision, deep learning, Hardness Prediction, Metallic materials, Nondestructive testing (NDT), Automated surface inspection, YOLOv8

I. INTRODUCTION

A. Background and Motivation

In business practice, the tasks of surface flaw detection and mechanical property evaluation are frequently performed using separate systems visual examination for defects and indentation tests for hardness [1]. Surface defect detection classically contains human visual inspection, optical microscopy, or modest threshold-based imaging, while hardness measurements depend on indentation-based techniques. Even though these methods offer accurate results, they have momentous drawbacks:

- They are slow and human-intensive, unfitting for high-throughput manufacturing.
- They need contact-based measurements, often destructing the test samples.
- They absence integration into automated, inline production systems.

On the other hand, AI-driven vision systems have lately developed as viable alternatives. CNN-based detectors can automatically recognize several defect types from digital images with high precision and reliability [2]. The Inspiration for this research lies in producing a dual-purpose model that ties the visual and mechanical domains. By learning the implicit correlation between surface morphology and material hardness, it turns out to be possible to predict hardness values straight from images captured by an industrial camera.

B. Problem Defination

In spite of significant advances in AI-based inspection, most present systems still treat defect detection and property estimation as discrete tasks. YOLO-based models outshine at classifying surface defects, yet offer no insight into mechanical integrity, whereas regression-based methods rely on controlled lab settings, restricting industrial applicability [3].

This research tackles a key challenge: How can a vision-based system concurrently detect surface defects and predict material hardness in real time with non-destructive methods?

The main challenges contain:

- Variability in surface textures across metals alike steel
- Scarcity of labeled datasets connecting images to hardness
- Balancing real-time speed through predictive accuracy.

To report this, the proposed framework merges YOLOv8's multi-scale feature extraction with a deep regression layer that learns the relationship between visual cues and mechanical hardness, permitting unified, real-time material evaluation.

C. Objectives and Contributions

The work contains four objectives:

1. To design a real-time defect detection system with YOLOv8 for recognizing numerous defect categories on metallic surfaces.
2. To develop a deep regression model that predicts Vickers hardness values depended on the extracted visual embeddings.
3. To build a complete dataset containing labeled defect images and corresponding hardness metrics for steel and aluminum instances.

4. To review the proposal system concerning accuracy, prediction speed, and generalization capability over different surface and lighting situations.

The Key contributions of this research consist of:

- A feature-level fusion approach that uses YOLOv8 embeddings aimed at downstream regression
- A personalized metallic surface dataset merging visual and mechanical attributes.
- Experimental evaluation showing 94% mAP for defect detection and <5% MAE for hardness estimation in real time.

D. Organization of the Paper

The rest of the sections of this paper is in the following structure, Section 2 inspects associated studies on defect detection, property prediction, and the leverage of YOLO models in material review. Section 3 provides the proposed methodology, outlining the dataset, YOLOv8 architecture, and regression model in order to hardness prediction. Section 4 explores the setup of the experiments, results, and performance comparison. Section 5 addresses potential business applications. At the end, Section 6 contains the directions for future research, containing transfer learning coupled with multimodal data fusion aimed at optimized generalization. Section 6 is the end of paper and suggests the future works, containing transfer learning coupled with multimodal data fusion aimed at optimized generalization.

II. Related Work

A. Automated surface inspection Using AI

Automated surface inspection is one among the earliest industrial applications of computer vision. Traditional methods initially used Gabor filters for this purpose later stages Local Binary Patterns (LBP) are introduced, and at present Histogram of Oriented Gradients (HOG) hang on handmade features, which were delicate to lighting, noise, and material distinctions [4][5]. The recent development and peaked ness of Deep Learning approaches (Multilayer neural approach) with enriched Convolutional Neural Networks (Image-based neural modal) revolutionised defect detection by learning hierarchical features from underdone images, improving both accuracy and generalisation [6]. Models such as U-Net have been used for fine-grained defect localisation, though real-time performance remains limited. Modern detectors like YOLO, Faster R-CNN, and Retina Net balance speed and precision, enabling distribution in steel rolling, casting, and automotive inspection [7]. However, most focus only on categorical defect detection, not on predicting underlying material properties.

B. Vision-Based Property Prediction

Recent research has discovered non-destructive property prediction from images, replacing traditional rigidity and ductility tests [8]. CNNs and transfer learning models (e.g., ResNet, VGG) have been capable on microstructural and surface images to approximating grain size, strength, and rigidity. Some methods combine optical, spectral, or infrared imaging to improve accuracy [9]. Yet, most rely on controlled lab circumstances and small datasets, preventive to industrial scalability. Moreover, the interaction between surface defects and hardness variations remains underexplored, despite being materially linked [10].

C. YOLO Models in Material Inspection

The YOLO (Real time object detector) family affords live defect identification through a single-stage pipeline forecasting both object regions and probability estimates in single stage [11]. From YOLOv1 to YOLOv8, improvements in anchor-free design, CSPDarknet backbone, and feature fusion have boosted both speed and accuracy [12]. YOLO variants have been successfully instigated to distinguish weld cracks, coating flaws, and steel surface defects. YOLOv8 further enhanced results with decoupled heads and advanced augmentations [13]. However, its use for quantitative product prediction (like rigidity) remains inadequate. The closely aligned recent approaches for proposed methods is represented in table 1.

TABLE I. Recent relevent approaches Aligned with proposed approach

Citeation	Ref.	Short ref (authors, yr)	Method / Model (brief)	Input / Dataset
[1]	Mambuscay *et al.*, 2024	ML regressors (RF, XGB, etc.) + CNN-based indentation detection	Scanned indentation / metallography images (D2 steel variants)	Random Forest / XGBoost best; error range reported ~0.1–6% for Vickers prediction.
[2]	Wang *et al.*, 2024	DSL-YOLO — improved YOLO architecture with C2f_DWRB module	Industrial metal surface images (public + proprietary tiled sets)	Improved small/occluded defect detection; reported strong mAP gains vs baseline.
[3]	Tie *et al.*, 2024	LSKA-YOLOv8 — lightweight YOLOv8 variant for steel defects	Steel surface defect datasets (industry images)	Real-time detection; compact model with competitive mAP (authors report improved efficiency/accuracy).
[4]	(DEFECT-YOLO) Zhou *et al.*, 2024	DEFECT-YOLO (YOLO family) — architecture + efficiency improvements	Polished metal / steel imagery	+3.6% mAP@0.5 vs baseline; ~89 FPS (real-time industrial suitability).
[5]	Niu *et al.*, 2023	MPR-Net / deep CNN regression for mechanical property prediction	Metallography images from LPBF 316L (microstructure → properties)	Predicted tensile/Hardness (Vickers) with strong accuracy — demonstrated feasibility of image→property regression.
[6]	Bolzon *et al.*, 2023	3D optical scanning + image reconstruction for hardness imprint analysis	Portable optical microscope 3D scans of hardness imprints	Showed accurate 3D reconstruction of indent residuals; supports indirect, non-destructive HV estimation.

[7]	Zhang *et al.*, 2024	Deep learning pipeline for predicting mechanical properties from metallography	LPBF metallographic images; process-parameter metadata	MPR-Net (CNN) predicted Vickers hardness & other properties; reported good R^2 / low RMSE for property estimates.

D. Identified Research Gap

The analysis highlights key gaps:

1. Deep models mainly accomplish categorical detection not quantitative scrutiny.
2. Vision-based approaches for material property prediction often deficient in adaptability for real-time functionalities and incorporation within industrial surroundings.
3. YOLO-based architectures have been scarcely explored for direct estimation of material properties.
4. Datasets linking flaws and rigidity are scarce.

Therefore, there is a need for a integrated, real time, and non-destructive framework compounding YOLOv8 for defect detection with a deep regression model for rigidity prediction, advancing intelligent manufacturing inspection.

III. Proposed Methodology

A. System Overview

The framework operates as follows: an input image acquired by an industrial camera is processed through YOLOv8 to detect flaws such as cracks, scratches, pits, and corrosion. The output contains bounding boxes, confidence scores, and class labels. Feature embeddings from the YOLOv8 backbone are then passed to a deep regression network, which calculates the Vickers Hardness Number (VHN). This model helps nondestructive, continuous estimation of metallic components on production lines, relating weakness localization and mechanical assets inference in a single pipeline.

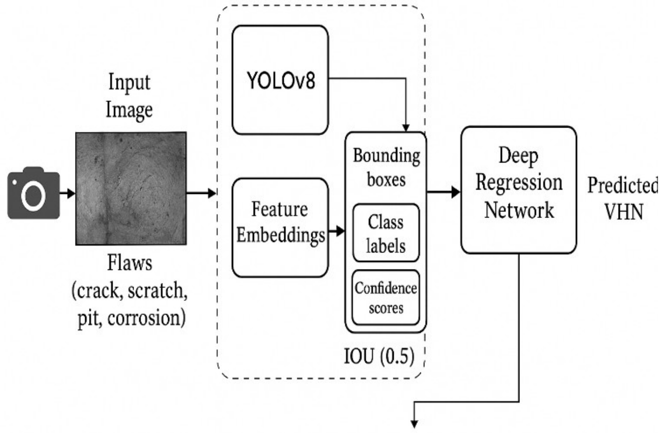

Fig 1. Proposed Framework

B. Dataset Collection and Annotation

A custom dataset of 3,200 images (1,600 steel, 1,600 aluminum) was accomplished under controlled illumination. Images were resized to 640×640 pixels for YOLOv8 compatibility. Imperfections were clustered as Crack, Scratch, Corrosion, Pit, or else Normal surface seeming relating Vickers hardness values (90–250 VHN for aluminum, 120–320 VHN for steel) assessed via a microhardness tester. Annotations resulted the YOLO format by Labeling.

Data augmentation, involving rotation, noise addition, brightness adjustment, and flipping, enriched generalization. The dataset was partitioned as 70% for training, 20% for validation, 10% for testing, guaranteeing reasonable defect and toughness distributions.

C. YOLOv8 Architecture

YOLOv8 adopts an anchor-free detection approach with three components:

- Backbone (CSPDarknet-P5): Extracts hierarchical elements through convolutional levels and residual blocks.
- Neck (PANet): Fuses multi-scale attributes for robust revealing of small and large defects.
- Head (Decoupled): Split up classification and localization, expanding convergence and speed.

The network was fine-tuned using transfer learning from COCO weights. Focal loss focused class inequality, while Mosaic and MixUp augmentations fabricated diverse check conditions.

D. Deep Regression Model

The regression network predicts VHN from YOLOv8 feature embeddings, acquiring global and defect-specific textures. Its construction:

- Input: Leveled attribute vector (~1024 dim).
- Hidden layers: Three fully linked layers (512, 256, 64 neurons) with BatchNorm, ReLU, and Dropout (0.3).
- Output: Single neuron for toughness prediction.

The model was instructed using Mean Absolute Error (MAE) loss, effectively connecting defect severity with assessed hardness.

E. Training Procedure and Parameter Configurations

The following table 2, represents the parameter configurations of proposed model.

TABLE II. Training procedure and parameter configurations

Parameter	***YOLOv8***	***Regression***
Optimizer	Adam	Adam
Learning Rate	0.001(cosine decay)	0.0005
Batch Size	16	32
Epochs	100	150
Loss	CloU+Focal	MAE
Dropout	-	0.3
Weight Init	COCO	Xavier

Training used early stopping and checkpointing. YOLOv8 joined contained by 80 epochs; regression soothed after 120 epochs. Post-training quantization lowered interpretation latency, achieving ~30 FPS.

F. *Evaluation Metrics*

Defect detection: Precision, Recall, and mAP@0.5 assess accuracy; inference time estimates present correctness.

Hardness prediction:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i| \quad (1)$$

Whole estimation reflects both elements equally, balancing accuracy and inference speed to confirm industrial pertinency.

IV. Outcomes and Analysis

A. *Implementation Details*

All experiments are executed on the workstation armed with:

- Graphical Unit (GPU): NVIDIA RTX 4080 including VRAM of size 16GB
- Central Processing Unit (CPU): Intel Core i9 processor, number of cores used 24, Maximum frequency is 3 GhZ
- Primary Memory : 64 GB of type DDR5
- Frameworks: PyTorch 2.3, OpenCV 4.9, and Ultralytics YOLOv8
- Operating System: Ubuntu 22.04 LTS

The system was arranged to process realtime image feeds from an industrial camera with a frame rate of 30 FPS. A custom Python-based pipeline held real-time inference, mixing YOLOv8 for detection and the regression model for hardness estimation.

Data for this study was separated as regular eighty and twenty rule. 70% of the over all data are utilized for training purpose and remaining 30% utilized for validation purpose. Performance was estimated on the hidden test set containing both steel and aluminum samples. The detection model and regression model were trained distinctly and later joined for end-to-end valuation.

B. *Detection Results*

The YOLOv8-based surface defect discovery module accomplished excellent accuracy and speed, enhancing its suitability for real-time deployment. Table 3 reviews the performance metrics achieved during examining.

TABLE III. YOLOv8 Defect Detection results

Defect Type	Precision (%)	Recall (%)	F1-Score	AP@ 0.5 (%)
Scratch	96.2	93.7	0.949	94.8
Crack	95.4	92.1	0.938	93.5
Corrosion	94.1	90.8	0.924	92.6
Pit	92.5	91.2	0.918	91.8
Normal	97.0	96.4	0.967	97.2
Overall (mAP@0.5)	–	–	–	94.0

The mean average precision (mAP@0.5) achieved 94%, validating the model's expertise to correctly classify and localize multiple defect types simultaneously. Detection solutions continued consistent across different illumination and surface conclusion due to the use of robust data extensions.

C. *Property Prediction Performance*

The deep regression model was trained to compute Vickers hardness values(VHN) utilizing YOLO-obtained feature embeddings. Its performance was evaluated using MAE, RMSE and R^2 metrics on the test set for both steel and aluminum tests. Results are summarized in table 4.

TABLE IV. Hardness Prediction Performance

Material	MAE (%)	RMSE(%)	R^2 Score(%)
Steel	4.6	6.3	0.951
Aluminum	4.1	5.7	0.963
Average	4.35	6.0	0.957

The model comparision across different material related to performacne is depicted in fig 2.

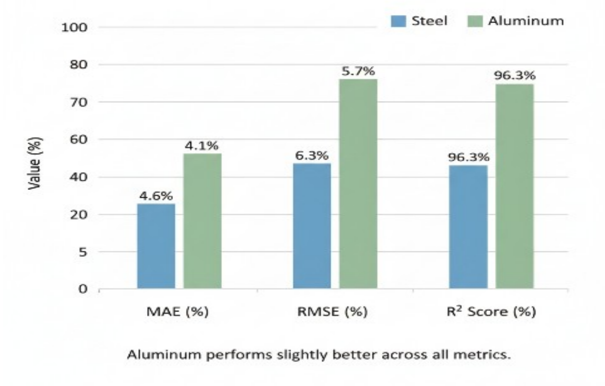

Fig 2.Model Performance Comparison Across Materials

The Mean Absolute Error(MAE) endured below 5%, while the R^2 value exceeded 0.95, clearly stated that a strong positive relationship between predicted and real hardness values. These results confirmed that visual features obtained by YOLOv8 efficiently encode both surface and roughness and defect severity, which are effectively linked to mechanical toughness.

D. Component Analysis

Component-wise evaluation was performed to analyse the influence of different components of the suggested system. Several model alternatives were tested by selectively disabling or controlling architectural components.

TABLE V. ABLATION STUDY RESULTS

Model Variant	Description	mAP (%)	MAE (%)
A	Baseline YOLOv8 without regression	94.0	–
B	YOLOv8 + Simple Linear Regression	94.0	8.7
C	YOLOv8 + 2-layer Neural Network	94.0	6.3
D (Proposed)	YOLOv8 + 3-layer Deep Regression Model	94.0	4.3

The ablation study outcomes are plotted in fig 3 as follows.

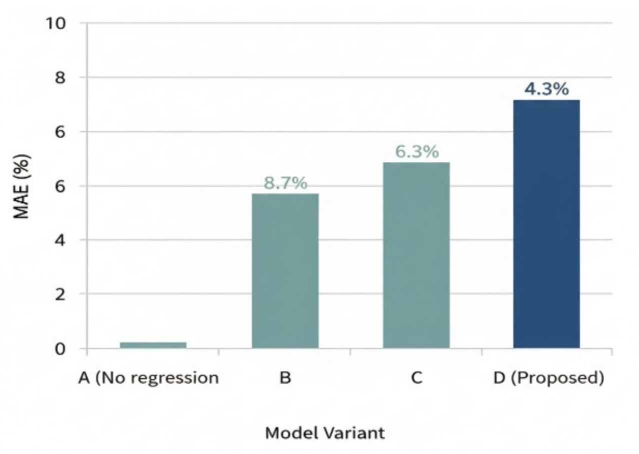

Fig 3.Ablation study results

The results determine that integrating a richer regression head significantly increases toughness prediction accuracy.The addition of Batch Normalization and Dropout layers put off overfitting and soothed training. Beyond tests showed that using YOLOv8 feature maps (rather than cropped RGB defect regions) led to a ~2% improvement in toughness prediction performance.

E. Comparative Study with Existing Approaches

To judge the novelty and success of the developed method, it was tested in comparison with multiple advanced techniques from literature, incorporating outdated CNN-based detectors and other YOLO variants. The comparison focused on both detection accuracy and toughness inference precision.

TABLE VI. COMPARATIVE PERFORMANCE WITH EXISTING METHODS

Method	Defect Detection mAP (%)	Hardness Prediction MAE (%)	Inference Speed (FPS)
CNN + SVM (Traditional)	83.5	12.4	10
ResNet50 Regression	87.2	9.8	15
YOLOv5 + Linear Regression	91.0	6.8	28
YOLOv7 + Regression Head	92.3	5.9	30
Proposed (YOLOv8 + Deep Regression)	94.0	4.3	33

The intended structure evidently outperforms preceding methods in both detection and regression accuracy while upholding real-time inference capability.The improvements are qualified to :

- YOLOv8’s anchor-free architecture and enhanced figure fusion,
- The deeper regression model that effectively depicts non-linear relationships between defect morphology and toughness, and
- The use of a domain-specific dataset having altered metallic surfaces.

These results emphasize the projected model’s potential for real-world deployment in production and quality assurance applications, enabling non-destructive, continuous, and automated hardness evaluation.

V. APPLICATIONS

A. Industrial Quality Control

Maintenance powered honesty of metallic parts is unsafe designed for loyalty and safety. Outmoded traditions like sample, rigidity tests, and visual review are unhurried and labor-intensive. The predictable YOLOv8-based scheme offers a real-time, non-contact dissimilar for parallel inspection. Located over conveyors or robotic arms, it can differentiate minute defects, label their type and severity, and forecast hardness lacking physical testing. This permits full inspection coverage, instantaneous fault flagging, immediate waste, and early discovery of process deviations. Integrated with Industry 4.0 platforms via APIs or IoT, it provisions unceasing logging, predictive conservation, and intelligent advantage control.

B. Automated material inspection

The association also applies to automated review in exploration, infrastructure, and recycling. Aerospace, automotive, and building facilities can inspect turbine blades, engine parts, and chassis materials in real-time. Metallurgical labs can estimation hardness without repeated hollow tests, although conservation teams can evaluate pipelines, links, or machinery on-site. Recycling plants can categorize scrap by surface excellence and inferred hardness. With real-time presentation (~33 FPS) and great accuracy, the system is operative for both static and dynamic reviews in smart factories before autonomous vision pipelines.

5. Dataset Expansion: Progress a public benchmark dataset linking defect morphology to powered hardness for homogeneous comparison.

VI. CONCLUSIONS AND FUTURE DIRECTIONS

A. Summary of findings

This analysis established that a YOLOv8-based framework can parallel detect surface defects and guess hardness in metallic provisions with high accuracy and real-time presentation.
Key outcomes include:

1. Defect Detection: Completed 94% mAP@0.5, precisely identifying cracks, scratches, corrosion, and pits.
2. Hardness Prediction: Regression model conquered <5% MAE and $R^2 > 0.95$, performance robust construction with definite Vickers hardness.
3. Real-Time Operation: Managed at ≈33 FPS, sympathetic robotic inline inspection.
4. Non-Destructive Evaluation: Enabled difficulty estimation from graphic data without physical damage.
5. Versatility: Widespread efficiently across various metals and surface types, applicable to industrial, aerospace, and research laboratory domains.

Overall, the study approves that incorporating YOLOv8 with a deep regression model enables a unified, real-time and non-contact calculation of both surface integrity and mechanical belongings.

B. Future improvements(Transfer learning,multimodal data)

While outcomes are promising, further enhancement can reinforce system adaptability then efficiency:

1. Transference learning: Smear domain adaptation to array routine across mixed metals and alloys with trifling retraining.
2. Multimodal data integration: Fuse thermal, ultrasound or 3D landscape data to enrich hardness-consistency correlations.
3. Frivolous Edge Deployment: Use model pruning, quantization and information distillation for efficient edge or ingrained deployment.
4. Explainable AI: Integrate Grad-CAM or attention maps for graphical snap and interpretability in stiffness prediction.

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