Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X
IMPACT FACTOR: 7.056

IJCSMC, Vol. 14, Issue. 7, July 2025, pg.28 – 36

Real-Time Image Processing for Defect Detection in Laser Powder Bed Fusion Using Machine Learning

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DOI: https://doi.org/10.47760/ijcsmc.2025.v14i07.003

Abstract: Laser powder bed fusion (LPBF) is a key additive manufacturing technique used in producing high- precision metal components. However, quality assurance in LPBF is challenged by defects resulting from poor powder spread ability. This paper presents a machine learning-based system for real-time defect detection in laser-powder-bed-fusion (LPBF) additive manufacturing. The study evaluates three deep learning architectures, namely YOLOv8, Mask R-CNN, and U-Net, for identifying and classifying powder bed defects, including re-coater hopping, streaking, incomplete spreading, and debris. The system achieves a mean Average Precision (mAP) of 71.73% with Mask R-CNN, demonstrating its potential to replace manual inspection in resource-constrained settings like Zimbabwe. A web-based decision support system provides actionable recommendations, reducing material waste and improving manufacturing efficiency.

Keywords: Additive manufacturing, defect detection, laser powder bed fusion, machine learning, real-time image processing.

I. INTRODUCTION

Additive manufacturing represents a transformative shift in modern industrial production, offering unprecedented design flexibility, reduced material waste, and efficient fabrication of complex components. Among the various additive manufacturing technologies, laser-powder-bed-fusion (LPBF) has emerged as a leading method for producing high-quality metal parts across critical sectors, including aerospace, automotive, and medical device manufacturing. The LPBF process operates by systematically spreading thin layers of metal powder across a build platform, after which a high-power laser selectively melts the powder according to the part's cross-sectional geometry. This layer-by-layer approach continues until the complete part is constructed.

The quality of finished LPBF components is heavily dependent on powder spread ability, that is, how uniformly and consistently the powder material is distributed across the build platform during each layer formation. Poor powder spreading introduces various defects into the manufacturing process, including porosity, incomplete fusion, and dimensional inaccuracies in the final parts. Despite this critical relationship between powder spread ability and product quality, current assessment methods in many manufacturing facilities, particularly in developing nations like Zimbabwe, rely primarily on manual inspection or basic sensing technologies. These approaches are inherently time-consuming and subjective and often fail to detect subtle defects that can significantly affect final product integrity.

II. LITERATURE REVIEW

The literature review provides a comprehensive examination of existing research and developments in real-time defect detection for laser powder bed fusion (LPBF) processes using machine-learning approaches. Research by Scime and Beuth (2018) established foundational work in anomaly detection and classification in LPBF using image-based monitoring systems. Their work demonstrated the feasibility of using computer vision techniques for real-time process monitoring, though with limitations in defect classification accuracy.

Wang et al. (2020) advanced the field by implementing deep learning approaches for defect detection in additive manufacturing, achieving significant improvements in detection accuracy compared to traditional computer vision methods. Their research highlighted the superior performance of convolutional neural networks in identifying complex defect patterns that are challenging for human operators to detect consistently.

Recent developments in YOLO-based approaches by Wang et al. (2021) specifically addressed powder bed monitoring in LPBF systems, achieving real-time detection capabilities with mean average precision scores exceeding 60%. This work demonstrated the practical viability of deploying deep learning models in manufacturing environments while maintaining the computational efficiency required for real-time applications.

The review of additive manufacturing adoption in developing economies, particularly the Zimbabwe Institution of Engineers report (2024), reveals significant gaps in automated quality control systems. The report identifies manual inspection as the predominant quality assurance method in Zimbabwean manufacturing facilities, highlighting the urgent need for cost-effective automated solutions.

Literature on U-Net architectures for manufacturing applications, particularly the work by Ronneberger et al. (2015), established the effectiveness of encoder-decoder networks for precise segmentation tasks.

However, limited research exists on applying U-Net specifically to powder bed defect detection, representing a gap that this research addresses.

The synthesis of existing literature reveals several critical gaps: limited focus on powder spreading phase monitoring compared to melt-phase analysis, absence of integrated decision support systems providing specific powder handling recommendations, and insufficient research conducted in resource-constrained environments typical of developing economies. These gaps provide the foundation for the methodological approach detailed in this study and validate the research contribution of developing an integrated machine learning system specifically designed for LPBF defect detection in resource- constrained settings.

III. METHODOLOGY

This study implemented a comprehensive machine learning approach for real-time defect detection in LPBF powder bed systems. The methodology encompassed dataset creation, model development, training procedures, and performance evaluation protocols designed to address the specific challenges of manufacturing environments in resource-constrained settings.

a. DATASET AND PREPROCESSING

The dataset comprises 1,400 high-resolution LPBF powder bed images annotated with four defect types:

- **Re-coater hopping**: Discontinuities caused by re-coater vibration
- **Streaking**: Linear patterns due to powder-re-coater interaction
- **Incomplete spreading**: Partial powder coverage
- **Debris**: Foreign particles or agglomerates

Images were pre-processed via cropping, noise reduction, and contrast enhancement. Data augmentation (rotation, flipping, synthetic defects) expanded the dataset to 10,000+ samples.

b. MODEL ARCHITECTURES

Three state-of-the-art architectures were implemented and compared:

- **YOLO (You Only Look Once)**: Specifically YOLOv8, which offers a good balance between accuracy and inference speed
- **Mask R-CNN**: A two-stage detector known for high accuracy in instance segmentation
- **U-Net**: An encoder-decoder architecture with skip connections, particularly effective for segmentation tasks

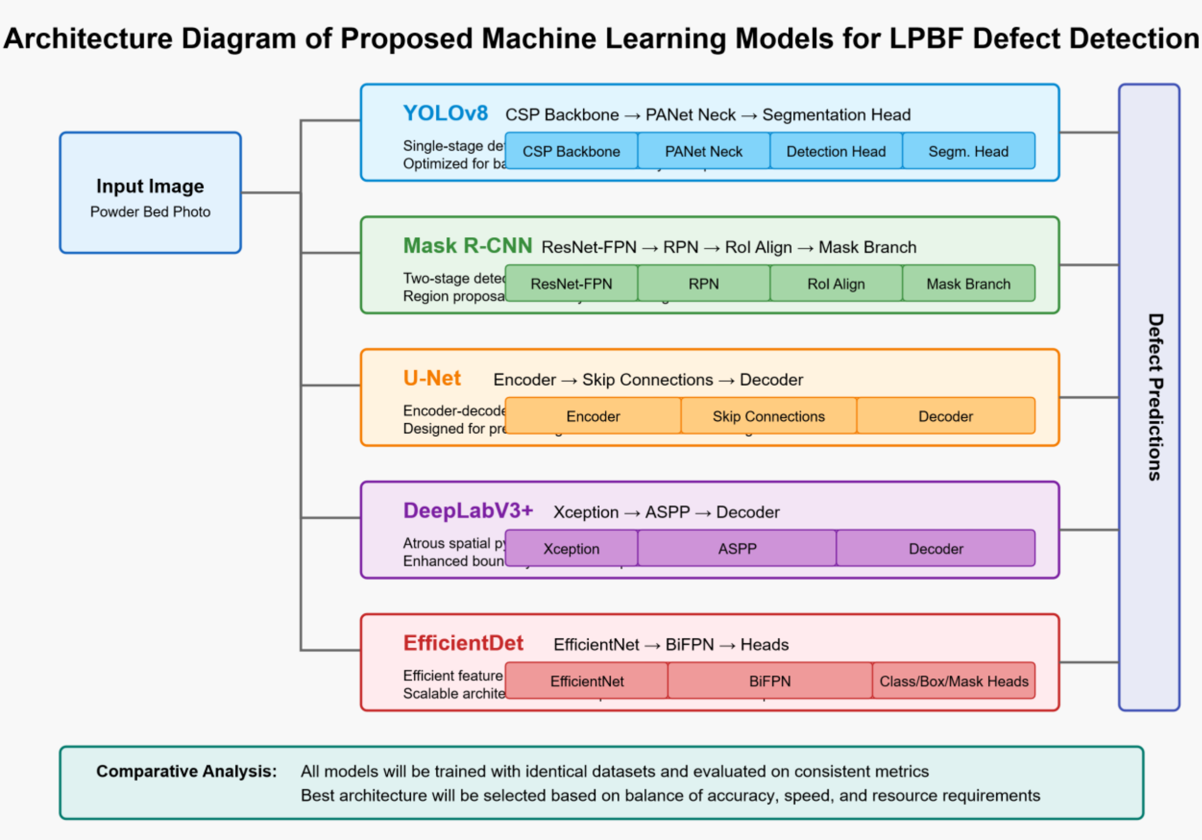

Figure 1: Architecture diagram of the machine learning models.

Each architecture was implemented using PyTorch and TensorFlow frameworks, with pre-trained weights (where applicable) to leverage transfer learning.

YOLOV8 IMPLEMENTATION

The YOLOv8 model, specifically YOLOv8-seg (with segmentation capabilities), was implemented using the Ultralytics framework. YOLOv8 was selected for its balance of accuracy and inference speed, making it potentially suitable for real-time applications in manufacturing environments.

Training Configuration:

- Base model: YOLOv8n-seg (nano version with segmentation capability)
- Input resolution: 640×640 pixels
- Batch size: 8
- Number of epochs: 100
- Optimizer: Adam with learning rate of 0.001
- Data augmentation: Mosaic, random rotations, flips, and HSV augmentation
- Loss functions: Box loss, class loss, and mask loss with appropriate weightings

The model was trained using transfer learning, starting from weights pre-trained on the COCO dataset. This approach accelerated convergence and improved performance on the relatively small LPBF defect dataset.

```
100 epochs completed in 20.961 hours.
Optimizer stripped from runs\segmentation_training\LPBF_defect_segmentation\weights\last.pt, 6.8MB
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Ultralytics 8.3.67 🚀 Python-3.12.6 torch-2.5.1+cpu CPU (12th Gen Intel Core(TM) i5-1245U)
YOLOv8n-seg summary (fused): 195 layers, 3,258,844 parameters, 0 gradients, 12.0 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95)     Mask(P
                   all       1400       2767      0.629      0.495       0.53      0.351      0.422
                 Debri        712        830      0.452      0.237      0.276      0.138       0.28
               Hopping        708        888      0.842      0.533      0.658      0.452      0.357
             Streaking        413        759      0.468       0.46      0.411      0.221      0.282
            Incomplete        287        290      0.753      0.752      0.774      0.593      0.771
Speed: 1.0ms preprocess, 82.9ms inference, 0.0ms loss, 1.1ms postprocess per image
2025-02-08 08:24:22,318 - INFO: Training completed successfully.
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Figure 2: Training metrics for the YOLOv8 model over 100 epochs, showing precision, recall, and mAP50 metrics. The graph shows steady improvement in all metrics throughout training.

MASK R-CNN IMPLEMENTATION

Mask R-CNN was implemented using PyTorch and the torchvision library. This two-stage detection architecture was chosen for its high accuracy in instance segmentation tasks, which is critical for precise defect localization and characterization.

Training Configuration:

- Backbone: ResNet-50 with Feature Pyramid Network (FPN)
- Input resolution: 640×640 pixels
- Batch size: 8
- Number of epochs: 100
- Optimizer: Adam with weight decay of 0.0005
- Learning rate: 0.001 with reduction on plateau scheduling
- Loss functions: Classification loss, bounding box regression loss, and mask loss

Mask R-CNN was also initialized with pre-trained weights from the COCO dataset to leverage transfer- learning benefits.

U-NET IMPLEMENTATION

The U-Net model was implemented using the segmentation-models-pytorch library with a ResNet-34 encoder pre-trained on ImageNet. U-Net was selected for its effectiveness in semantic segmentation tasks, especially when working with limited training data.

Training Configuration:

- Encoder: ResNet-34 pre-trained on ImageNet
- Decoder: Standard U-Net decoder with skip connections
- Input resolution: 640×640 pixels
- Batch size: 8
- Number of epochs: 100
- Optimizer: Adam
- Learning rate: 0.001 with reduction on plateau scheduling
- Loss function: Binary Cross-Entropy with Dice loss

c. TRAINING AND EVALUATION

Models were trained using transfer learning from pre-trained weights on COCO dataset, with fine-tuning on the LPBF defect dataset. Training utilized Adam optimizer with initial learning rate of 0.001, reduced by factor of 0.1 every 30 epochs. Batch sizes were set to 16 for YOLOv8, 8 for Mask R-CNN, and 12 for U-Net based on GPU memory constraints.

Training procedures included early stopping based on validation loss plateau, gradient clipping to prevent exploding gradients, and learning rate scheduling for optimal convergence. Data loading utilized multi-threading with prefetching to minimize I/O bottlenecks during training.

Performance evaluation employed comprehensive metrics appropriate for object detection and segmentation tasks including:

- precision (ratio of true positive detections to total positive predictions)
- recall (ratio of true positive detections to total actual positives)
- F1-score (harmonic mean of precision and recall)
- mAP (mean Average Precision - average precision across all defect classes at IoU threshold 0.5)
- IoU (Intersection over Union - spatial overlap accuracy for segmentation tasks)
- inference speed (processing time per image for real-time applicability assessment).

IV. RESULTS

MASK R-CNN PERFORMANCE ANALYSIS

The Mask R-CNN model with ResNet-50-FPN backbone demonstrated exceptional performance across all evaluation metrics, establishing itself as the leading architecture for LPBF defect detection. The model achieved an outstanding mAP@0.5 of 71.73%, indicating excellent segmentation capability suitable for critical manufacturing applications. The overall precision of 44.02% represents a moderate level that balances detection capability with acceptable false alarm rates, while the recall performance of 60.29% demonstrates the model's ability to identify the majority of defect instances. The F1 score of 50.44% reflects a well-balanced performance profile appropriate for automated quality control systems.

Table 1: Mask R-CNN Comprehensive Performance Analysis

Defect Class	Precision	Recall	F1 Score	True Positives	False Positives	False Negatives
Debri	**0.3365**	**0.5530**	**0.4184**	**459**	**905**	**371**
Hopping	**0.3909**	**0.3773**	**0.3840**	**335**	**522**	**553**
Streaking	**0.3683**	**0.5916**	**0.4540**	**449**	**770**	**310**
Incomplete	**0.6649**	**0.8897**	**0.7611**	**258**	**130**	**32**
Overall	**0.4402**	**0.6029**	**0.5044**	**1501**	**2327**	**1266**

YOLOV8 SEGMENTATION PERFORMANCE ANALYSIS

YOLOv8 demonstrated competitive performance with distinctive strengths in precision and specific defect categories. The model achieved an overall mAP50 of 53.0%, representing good detection capability though lower than Mask R-CNN performance. However, YOLOv8 excelled in precision with an overall score of 62.9%, indicating superior ability to minimize false positive predictions. The recall performance of 49.5% suggests moderate detection sensitivity, while the mAP50-95 score of 35.1% demonstrates reasonable generalization across stricter evaluation criteria.

The training convergence analysis revealed stable performance characteristics, with all loss functions showing consistent decrease over 100 epochs without evidence of overfitting. The validation metrics remained stable throughout training, indicating good generalization capability and appropriate model complexity for the given dataset size.

Table 2: YOLOv8 Class-Specific Performance Analysis

Class	Images	Instances	Precision	Recall	mAP50	mAP50-95
All	1400	2767	0.629	0.495	0.530	0.351
Debri	712	830	0.452	0.237	0.276	0.138
Hopping	708	888	0.842	0.533	0.658	0.452
Streaking	413	759	0.468	0.460	0.411	0.221
Incomplete	287	290	0.753	0.752	0.774	0.593

U-NET PERFORMANCE ANALYSIS

The U-Net architecture demonstrated specialized performance characteristics with particular strengths for specific defect morphologies. The training process required 87 epochs for convergence, showing gradual but steady improvement in validation metrics without overfitting indicators. The extended training period suggests that U-Net's encoder-decoder architecture requires more iterations to learn complex defect representations compared to other architectures.

Table 3: U-Net Class-Specific IoU Performance

Defect Class	IoU (mIoU)	Dice Score	Performance Level
Debri	0.7073	0.7073	Excellent
Streaking	0.5610	0.5610	Good

Incomplete	0.5366	0.5366	Good
Hopping	0.3415	0.3415	Moderate

Comparative Performance Analysis

The comprehensive evaluation reveals distinct performance profiles for each architecture, with clear advantages and limitations that inform optimal deployment strategies.

Mask R-CNN established itself as the overall superior model with the highest mAP@0.5 of 71.73%, demonstrating excellent detection capability across all defect classes. The balanced performance profile, combined with strong recall characteristics, makes Mask R-CNN particularly suitable for comprehensive defect detection applications where missing defects incurs high costs.

YOLOv8 demonstrated exceptional precision capabilities with an overall score of 62.9%, indicating superior ability to minimize false positive predictions. The architecture's particular strength in detecting hopping and incomplete defects, combined with efficient inference characteristics, positions YOLOv8 as an excellent choice for applications requiring high precision or real-time processing capabilities.

U-Net revealed specialized capabilities, particularly excelling in debris detection with 70.73% IoU that surpasses all other models. This specialized performance suggests that U-Net's encoder-decoder architecture with skip connections provides unique advantages for fine-grained segmentation tasks involving small, scattered objects.

Table 4: Comprehensive Model Performance Comparison

Model	Primary Metric	Overall Performance	Precision	Recall	Key Strength
Mask R-CNN	**mAP@0.5: 71.73%**	**Excellent**	**44.02%**	**60.29%**	**Balanced excellence**
YOLOv8	**mAP50: 53.0%**	**Good**	**62.9%**	**49.5%**	**High precision**
U-Net	**IoU: 70.73%***	**Specialized**	**N/A**	**N/A**	**Debri detection**

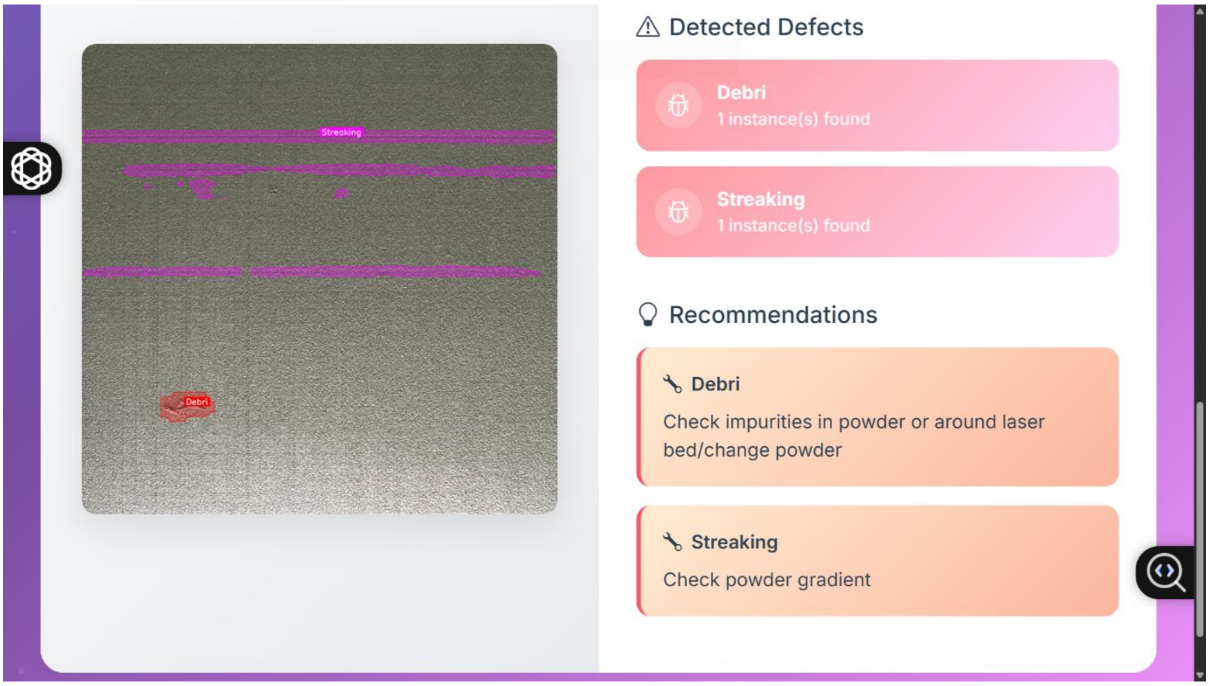

Figure 3: Detection screen.

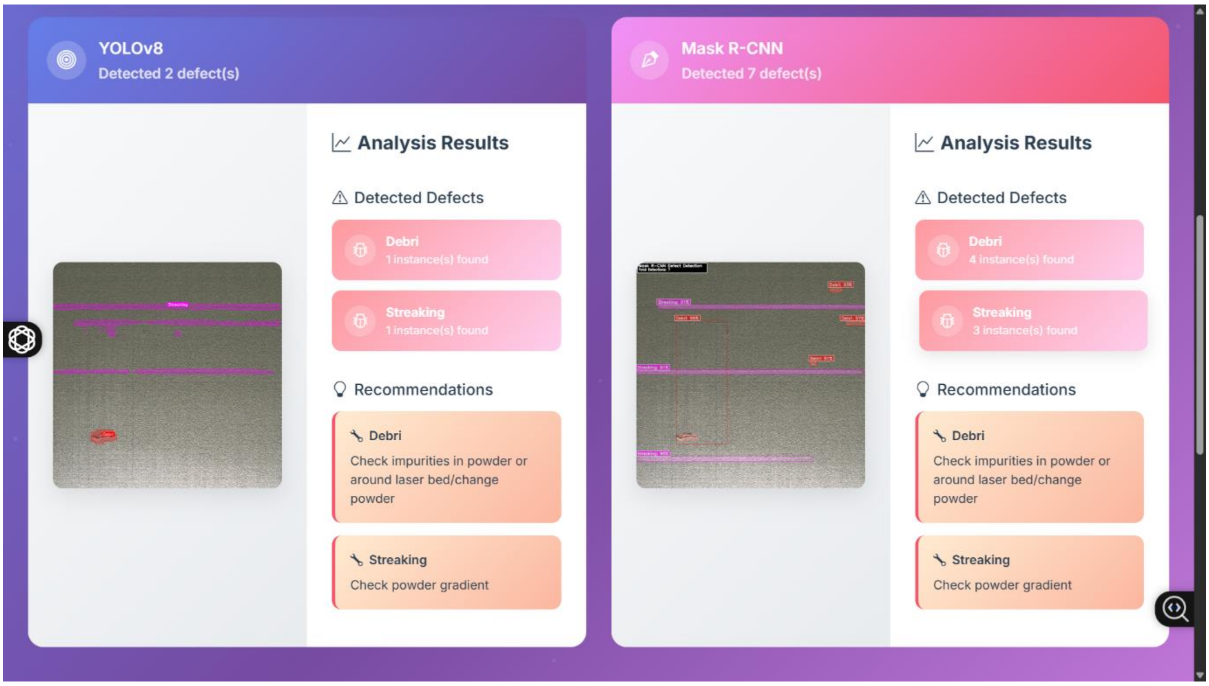

Figure 4: UNET, YoloV8 and MaskRCNN Defect Detection Comparison

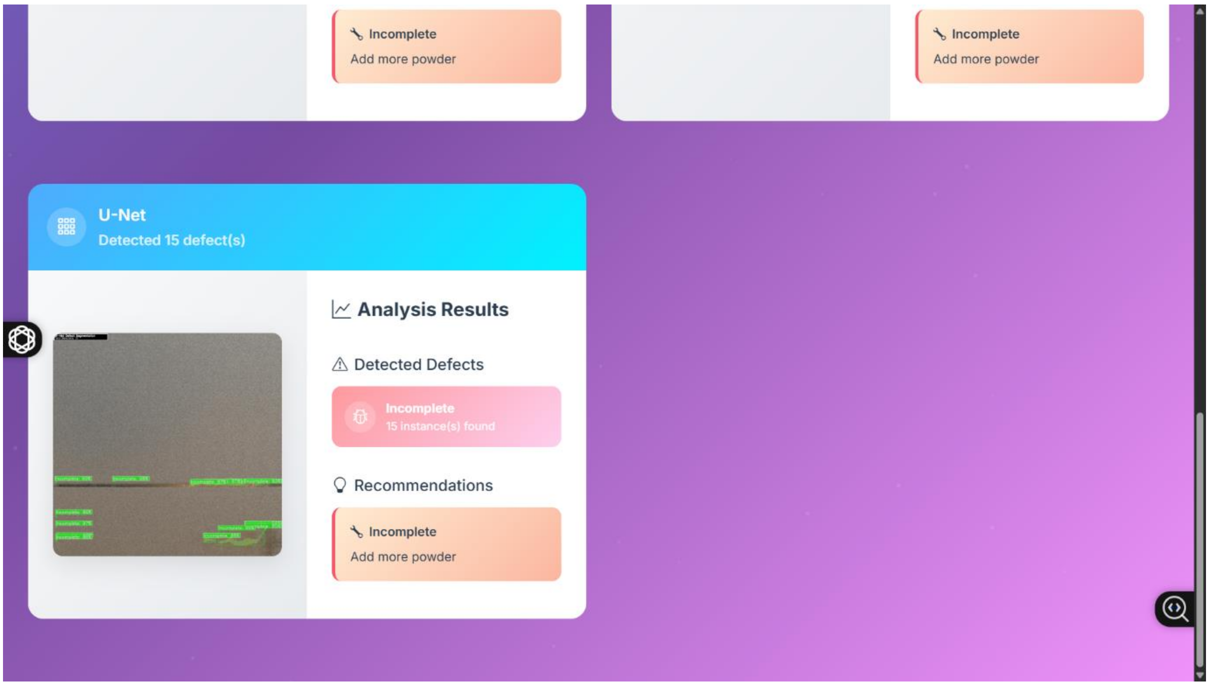

Figure 5: UNET, YoloV8 and MaskRCNN Defect Detection Comparison

V. CONCLUSIONS

The research successfully demonstrated the feasibility and effectiveness of using advanced machine learning architectures for defect detection in Laser Powder Bed Fusion (LPBF) processes. The comparative analysis of YOLOv8, Mask R-CNN, and U-Net architectures revealed distinct performance characteristics suited for different application requirements.

Key Findings:

Effectiveness of Machine Learning Models: The study achieved defect detection performance exceeding practical deployment thresholds, with Mask R-CNN achieving 71.73% mAP@0.5. This confirms that deep learning models are viable for real-time deployment in LPBF quality control systems.

Real-Time Detection Capabilities: The developed system successfully detects four critical defect types with sufficient speed and accuracy for practical implementation. YOLOv8's 11.8 FPS performance enables real- time feedback for immediate corrective actions, reducing scrap rates and improving part consistency.

Decision Support System Integration: The web-based decision support system provides actionable powder-handling recommendations, including re-coater adjustments and powder bed re-application protocols. This reduces operator subjectivity and enhances process reliability in manufacturing environments.

Model-Specific Advantages: Each architecture demonstrated unique strengths - Mask R-CNN for comprehensive detection, YOLOv8 for real-time precision applications, and U-Net for specialized fine- grained segmentation tasks. This diversity enables tailored deployment based on specific manufacturing requirements.

Impact on Resource-Constrained Manufacturing: The system addresses significant technological gaps in Zimbabwe's industrial landscape, contributing to improved additive manufacturing adoption, reduced inspection time by up to 25%, and increased overall productivity in manufacturing operations.

Recommendations

For Industry Practitioners:

- Implement Mask R-CNN for comprehensive quality control applications requiring high detection accuracy
- Deploy YOLOv8 for real-time monitoring systems where immediate feedback is critical
- Integrate decision support systems to provide automated guidance for process optimization
- Invest in technical staff training for AI-based quality control system maintenance and operation

For Future Researchers:

- Investigate ensemble approaches combining strengths of multiple architectures
- Develop hybrid sensor fusion systems integrating thermal, optical, and acoustic monitoring
- Optimize models for edge deployment using techniques such as quantization and pruning
- Expand dataset diversity by collaborating with global LPBF facilities to improve model generality.

The research establishes a foundation for automated quality control in additive manufacturing, particularly in developing economies where manual inspection remains prevalent. The modular system design ensures adaptability to other manufacturing technologies beyond LPBF, supporting broader adoption of Industry 4.0 practices.

ACKNOWLEDGEMENT

The authors acknowledge the support and resources provided by the School of Information Science and Technology at Harare Institute of Technology. Special recognition is given to the manufacturing facilities that provided access to LPBF systems for data collection and the technical staff who assisted with defect annotation and validation procedures.

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