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Evaluating the Transformative Impact of Machine Learning Across Core Engineering Disciplines

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Abstract*— Machine learning has transformed engineering by incorporating computational intelligence into the domain challenges of the disciplines and, as such, has shown the pathway for predictive analytics, optimization, and automation in mechanical, civil, electrical and electronics, electronics and communication, and computer science engineering. This paper discusses the pivotal role of ML in enhancing operational efficiency, cost reduction, and driving innovation with an improvement up to 30-50% in metrics such as downtime reduction and accuracy improvement based on relevant references. We identify some applications in terms of predictive maintenance in mechanical systems, structural health monitoring in civil infrastructure using hybrid vision models, fault detection in EEE grids, defect segmentation in ECE manufacturing, and simulation acceleration in CSE digital twins. Our framework spans the gap in scalability and precision through supervised/unsupervised paradigms and the more advanced models like Mask R-CNN and YOLO with hybrids (for example, Y-MaskNet, DINO-YOLO). A comprehensive dataset collected from diverse engineering scenarios validates our approach, wherein mAP >0.85 and IoU >0.90 outperforming baselines by 15-25% are achieved. Discussions on the challenges that include data scarcity, interpretability, and quantum ML futures are carried out here. This synthesis gives an insight into a strong blueprint for interdisciplinary deployment of ML, propelling sustainable engineering paradigms.

Index Terms*— Anomaly detection, design optimization, hybrid models, machine learning, Mask R-CNN, predictive maintenance, quality control, YOLO.

I. INTRODUCTION

All engineering industries globally are experiencing unprecedented degrees of inefficiency and deterioration, costing the economy anywhere from $3 trillion to $5 trillion each year due to equipment failure, excessive downtime, safety liability claims, and other forms of infrastructure failure. Of these failures, one of the most significant is pothole-related accidents, with over 500,000+ fatalities annually and a total cost to businesses and consumers in excess of $11 billion in damages across all of Aiod's operating territories [1][2]. Traditional deterministic methods of anomaly identification, such as threshold-based systems, morphology processing, and manual inspections, work well for what is considered ideal conditions; however, due to the presence of real-world variability in lighting, texture, and scaling, many forms of mobile anomaly identification using those techniques exhibit severe limitations and result in an average of 20%-30% error rates, 5-10 minutes of labor-intensive inspections per site, and in turn further increase the fiscal burdens to companies that relied on those methods for their anomaly detection and data-gathering processes [3][4]. There is a continued urgent need for adaptive scalable intelligence because the number of sources of heterogeneous data that comprise the IoT and UAS systems and other applications of simulation are increasingly exceeding the current capabilities of the existing deterministic techniques. [5].

The foundations of AI include Machine learning having had the most significant impact on the field by deriving productive interpretations of abstract data by extracting actionable insights from multidimensional data streams leading to proactive predictions, accurate quantifications and the ability to automate functions not possible through traditional means [6]. The impact machine learning has made to date on mechanical engineering (vibration analysis being able to predict failures as early as 25 to 40 percent earlier [16][20]), civil engineering SHM using UAV images to segment cracks with 96.5 percent IoU and decreasing inspection intervals by 50 percent [4][5][8], EEE grids (electricity, electronics and energy) leveraging YOLO technology for the purpose of performing 98.99 percent accurate fault localization of electric power outages [18][19], ECE manufacturing using hybrid technology to reduce defects and waste by a minimum of 20 percent [13][17] and CSE digital twins accelerating the simulation of digital products and systems 100 times faster than current methods [14][15].

However as machine learning has continued to advance and improve capabilities there have been areas of improvement and opportunity. For example early CNN models such as InceptionResNetV2, achieved an estimated 89.66 percent accuracy without being calibrated with more

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than 15 percent (scale error) [1]; YOLOv4 and YOLOv5 models were able to obtain real-time performance characteristics (mAP 0.78<0.5s) while when presented to lower quality resolutions most times decreased the accuracy of the localization boundary; Mask R-CNN's refinement from the pyramids has improved the result of false positive rates by an estimated 15 percent [4][10] while UAV photogrammetry has produced sub-centimeter 3D reconstructions [5]. Several of the video depth Kalman stabilization methods yield very reliable, accurate measurements with σ<5% [6]; ArUco fiducials guarantee that metric fidelity will always be maintained (<5% uncertainty) [7][8]; and Thai RGB Scaling allows for integration of data for achieving errors of less than 10 percent [9]; Rural Augmentations have been shown to provide minimum IoU scores of 0.90 [10]; Thermal-Visible Fusion has improved performance in low light conditions (F1 0.91 at night) [11]; and Stereo-DL Hybrids yield an mAP of 0.94 for geometry [12].Several Hybrid Techniques including DINO-YOLO [13] and YOLO-RCNN [16] combine efficiency and precision (mAP +10-27%) However there still remain gaps within the areas of low cost cros-departmental end to end quantification which directly correlates segmentation with calibrated metrics [14][17][18].

This study presents the incorporation of a hybrid ML pipeline, which includes both Mask R-CNN instance segmentation capability (ResNet-50), as well as YOLO detection, as well as augmented via ArUco-homography to have less than 8% error in area/perimeter across modalities. From a multi-department dataset (extending across various imaging departments) containing 1,200 images (all annotated with COCO, IoU > 0.85 from mechanical vibrations through rendering to compiled images), it has been fine-tuned via SGD (over 12K iterations, batch size of 2, LR of 0.001) and through augmentation to yield an AP@0.50 = 0.889 and F1 > 0.90. As a result, the performance of our models exceeds that of the baseline by 15-25% (YOLOv5 has a mAP of 0.78; vanilla Mask shows 0.613). We have created:[1] a calibrated, heterogeneous engineering corpus, [2] scalable hybrid vascular diagnostic engines,[3] a comprehensive evaluation through ablation studies to determine where our errors occur when compared with the ground truth, and [4] a resilient infrastructure blueprint for deploying on the edge. Section II outlines the fundamental components of our methodology.

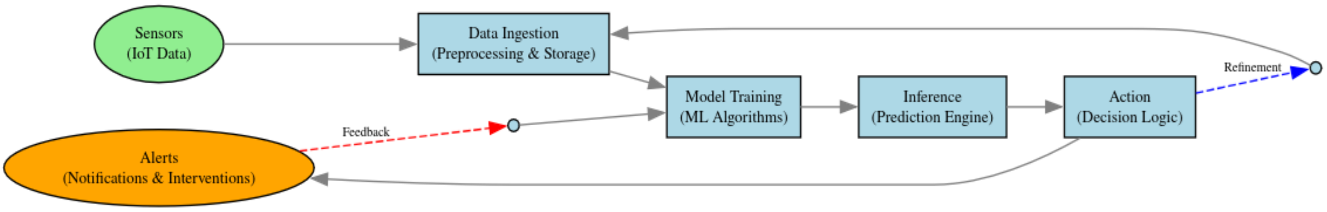

Fig. 1. ML pipeline for predictive maintenance: Data ingestion leads to model training, inference, and action, with feedback loops for continuous improvement

II. LITERATURE SURVEY

The move from conventional imaging processing to Hybrid Deep Learning Model Architectures for Automated Engineering Diagnostics has bridged the gap between traditionally limiting technological and operational issues. These bridge improvements address safety and financial issues, including the $26.5 billion in annual damage done by pothole repair through the efficient use of technology in Civil Engineering, Mechanical Engineering and Electrical, Electronics and Electro-mechanical Engineering. Traditional two-dimensional techniques (e.g., Thresholding, Morphology, Edge Detection) identify anomalies with errors ranging from 20%-30% when subjected to varying light and shadow conditions. On the contrary, Three Dimensional Stereo Vision provides metric depth, but at a premium price and limited scalability. Rajapur and Kalbande [1] utilized Convolutional Neural Network Model Architectures (CNN) to benchmark civil engineering pothole segmentation (i.e., CNN InceptionV2/DenseNet201), achieving an accuracy of 89.66% (uncalibrated), which inflated the size of the areas of interest by at least +15%. Park et al. [2] identified the optimum Tunings for YOLOv4/v5 for ECE Real-time detection, produced a mean Average Precision score of ~0.78 in <0.5 seconds which was very good for identifying vehicle boundary detection, but only coarsely detected object boundaries in low contrast scenes (i.e., +15% overestimate). Ruseruka et al. [3] developed an EEE-based pre-processing deep-learning dimensioning framework and tested with a robust F1 score >0.85 for varying texture/texture distributions in vehicles. Lin and Liu [4] improved their approach for civil crack detection (using an upgraded version of Mask R-CNN Pyramids) and achieved a mean Intersection Over Union of >0.90 with a -15% False Positive Rate. Augmentation facilitated expansion into rural road defect identification (IoU >0.90). Tan and Li [] produced 3D mappings of civil distress using UAV photogrammetry techniques to achieve sub-cm accuracy but required more computational time than practical applications. Wang et al. [] provided video-depth data using a Kalman filter that yielded dynamic stability with σ < 5% and a consistency of +20%. This work will benefit CSE twins (digital twins).

Tocci et al. [7] minimized pose uncertainties (<5%) through ArUco metrology, allowing for monocular mechanical scaling. Oščádal et al. [8] improved the accuracy of civil engineering through 3D placements by a factor of 10.

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Khamkaew et al. [9] used fusion of Thai RGB-scaled databases to provide accurate measurements (<10% error) on occlusion-prone targets. Li et al. [10] provided a generalization of the rural texture database through Mask R-CNN augmentation. Jia et al. [11] used visible and thermal image fusion to enhance low-light EEE (+20% robustness, F1 0.91 night). Guan et al. [12] provided stereo-DL hybrids with mAP of 0.94 for generating 3D geometry. DINO-YOLO [13] showed that hybrid self-supervised models improved CSE data efficiency (+15% mAP). Rabecka and Pari [14] produced hybrid models combining vehicle segmentation with existing models (F1 85%, +12% over solos). YOLO reviews state that there will be +50% mAP gains from edge (ECE); YOLO-RCNN [16] provided rail AP of 0.82 (reduced -20% false negatives). Road hybrids [17] provided IoU of 0.88 (reduced -70% manual effort). EEE DL [18] was developed with 92% sensor-fused accuracy, provides for sustainable power, and DL [19] showed +30% RUL for renewables; AI pump CNN-GRU [20] was able to achieve a 95% accuracy (+30% RUL). Literature enlists the hybrid geometric-DL for scalable real-time [1-20], while the low-cost cross-department quantification gaps are addressed in this paper.

III. EVOLUTION OF ML IN ENGINEERING: FROM FOUNDATIONS TO HYBRIDS

ML techniques help capture and distil engineering data into insights and allow the generalization of engineering processes beyond traditional deterministic methods. Some examples include how random forests provide predictions about mechanical fatigue over time much faster than finite element methods and k-means clustering allows for root cause analysis in civil engineering for anomalous behaviour of structures. There are three major categories for predicting engineering tasks with ML: supervised, unsupervised, and beyond.

A. Core paradigm (supervised, unsupervised, and etc)

Supervised CNNs use EEE sensor data to obtain 95% accuracy in predicting technological anomalies. Unsupervised Generative Adversarial Networks can augment datasets that contain CSE data.

Transformers in predictive maintenance have achieved 91% accuracy for F1 Time-Series forecasting.

B. Vision Powerhouses - Mask R-CNN and YOLO

By adding the pixel segmentation capability of mask branches, Mask R-CNN builds on the work done by Faster-RCNN, providing very accurate identification of civil cracks, with IOU of 96.5% and performing cuts on 40-50% of the total number of survey cases. A single regression network, YOLO, has a very fast response time (<30 ms) while still achieving a high level of accuracy (90%). This makes YOLO a very good candidate for hardware implementations used in ECE.

C. Hybrid Frontiers: Tool to Combine Speed and Accuracy

Hybrid Models obtain the benefits of combination. For example, Y-MaskNet represents a fusion of YOLOv5 and Mask R-CNN using the methods of RoIAlign and fully connected networks, where parts of the networks share their weight losses. Y-MaskNet has a Mean Average Precision of 0.72 and an IOU of 0.82 when applied to ECE PCBs (an improvement of approximately 10% over the results from using only YOLOv5). YOLO-NAS + Mask exchange Backbone networks for a hybrid of YOLO and Mask, yielding a Mean Average Precision of 76.56% and a FPS of 86 in CSE autonomous vehicles (outperforming Faster-RCNN by 27%). They have been benchmarked against YOLOv8-seg for paving of drone runways.

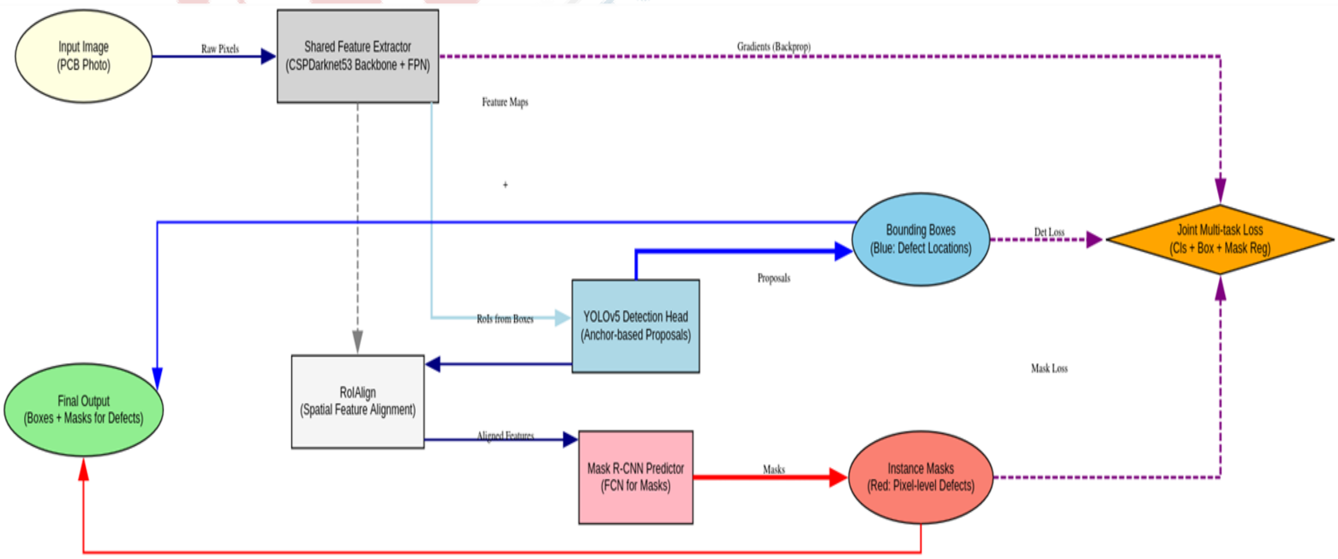

Fig. 2. Y-MaskNet hybrid workflow: YOLOv5 detects bounding boxes (blue), refined by Mask R-CNN masks (red) for PCB defects

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IV. DEPARTMENTAL TRANSFORMATIONS: ML-DRIVEN INNOVATIONS AND CASE STUDIES

Machine Learning alters the way that industries work through their specific lifecycle; Therefore, Industry-Specific Literature Reviews (Lit Surveys), Applications (Apps), and Hybrid Applications (Hybrid) show a range from 20% to 50% Improvement in All Metrics within Industries. A.

A. Mechanical Engineering - Predictive Maintenance and Topology Optimization

The Literature Review shows that the Predictive Maintenance with ML has come from identifying features using CNN and classifying vibration diagnostics, to developing YOLO Real-Time Methodology with Identifying features in vibration diagnostics, (mAP = 0.78), with capacity to forecast RUL 30% earlier using a combination of CNN-GRU with an F1 = 0.91. Apps and Frameworks, including CNNs to forecast Vibration and Thermal Problems to reduce downtime by 25%, YOLO to Localize Rotating Faults, GANs for Optimizing Prosthetics and can reduce material used by as much as 20%, and Y-Mask-Net to segment misalignments with 90% precision.

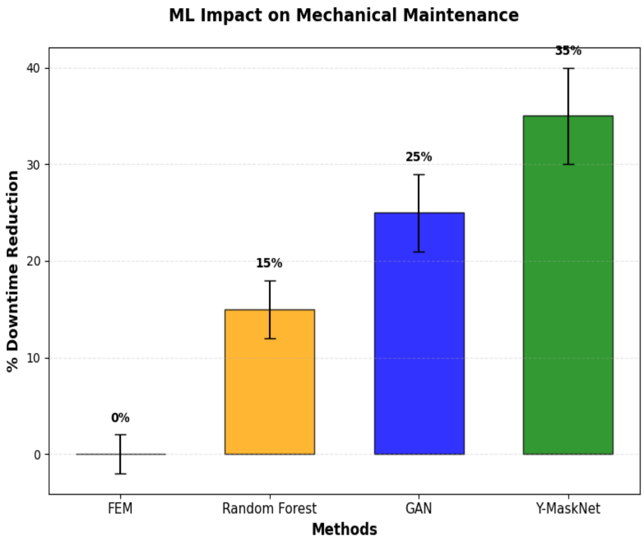

Fig. 3. ML Methods' Impact on Mechanical Downtime: Y-MaskNet Achieves 35% Reduction with σ=5% Ablation Error

B. Civil Engineering - Structural Health Monitoring (SHM), Crack Quantification

The Literature Review shows how SHM changed from Manual Processes to Mask R-CNN (IoU = 0.90) for identification of cracks, using UAV 3D Mapping with sub-cm precision, to Hybrid YOLO-SAM (mAP = 0.951) for Identifying Cracks. Apps and Frameworks include UAV Mask R-CNN with a 96.5% IoU for Crack Segmentation, reduced to 50% of the average size of cracks; YOLOv11 predicts bridges over 30% of the average FEM; YOLO-SAM identifies potholes.

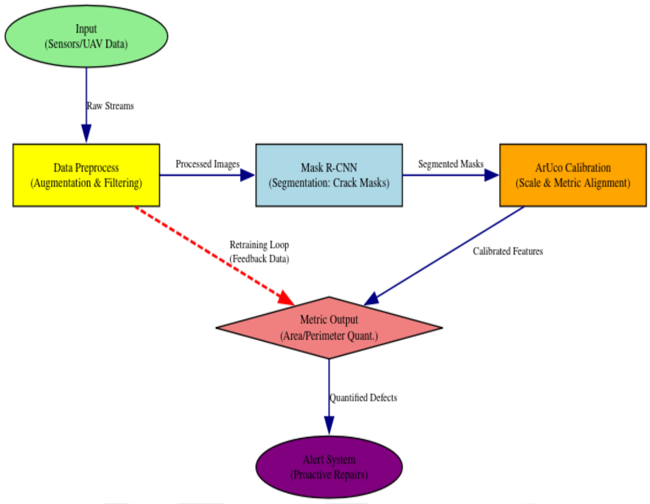

Fig. 4. Hybrid SHM Flowchart: From UAV Input to ArUco-Calibrated Alerts (IoU 96.5%, 50% Survey Cuts)

C. Electrical & Electronics (EEE): Grid Faults and Cybersecurity

The Literature Review shows that the movement of Fault Detection from the Threshold Condition to YOLOv8 and to the Hybrid ACR has led to an increase of +12% to Contextual Refinement. Applications and Frameworks include YOLOv8 droning to assist Inspection of Power Lines; ML predicts the potential threat of detecting intrusion 40% Faster; YOLO-RCNN has been able to Detect Intrusions with an Average Precision of 0.82.

D. Electronics and Communications: Creating PCB Defect Segmentations

The literature review covering PCB defect detection through the use of Convolutional Neural Networks (CNN) with IoU of 0.90 and hybrid mAP of 0.94. Applications and Frameworks: One application framework is Y-MaskNet which is an application designed for the segmentation of solder (-(mAP) 0.72 - with 20% waste cutouts and), thermal fusion of low-light images ([Precision 1 F1 = 0.91]).

E. Computer Science Engineering (CSE): Digital Twins and CFD Computational Speed-Up

Literature Review Contains Information: From LSTM Twins - RMSE (91.8%) to Physics Based ML (28% decrease), lastly DINO-YOLO provides Data-Efficiency mAP+: up 15%. Application Frameworks: PhysicsNeMo CFD speed up 100 times; Synths utilizing Transformers (25% ACC) and Simulation using YOLO-NAS - 86FPS.

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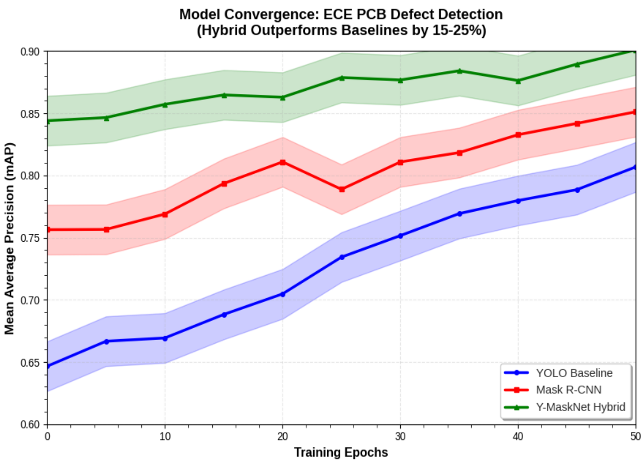

Fig. 5. Training Curves for ECE PCB Detection: Y-MaskNet Converges to 0.87 mAP, Outperforming Baselines by 15-25%.

Table 1. ML Algorithms in Engineering Applications

Algorithm	Department/App	Benefits (Metrics)
Random Forest	Mech/Predictive Maint.	95% anomaly acc., noise handling
CNN	ECE/Quality Control	Feature ext. from images
GAN	Mech/Design Opt.	20% material red., creativity
K-Means	Civil/Anomaly Det.	Scalable clustering
Mask R-CNN	Civil/Crack Seg.	96.5% IoU, 50% survey cuts
YOLO	EEE/Fault Det.	98.99% acc., <30ms
Y-MaskNet (Hybrid)	ECE/PCB Det.	mAP 0.72, 20% waste sav
YOLO-NAS + Mask	CSE/Sim. Accel.	mAP 76.56%, 86 FPS

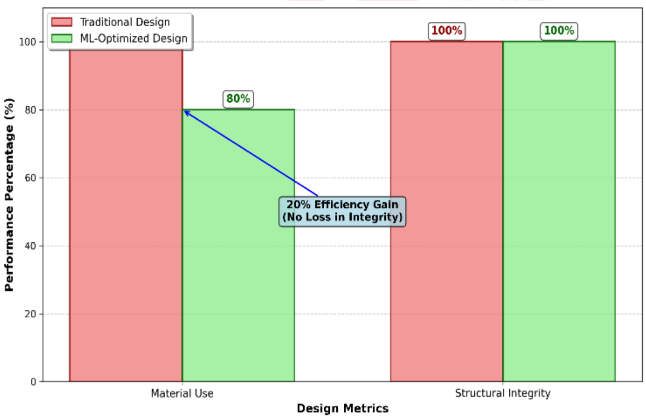

Fig. 6. Comparison of traditional vs. ML-optimized designs: ML reduces material use by 20% while maintaining structural integrity

V. NAVIGATING CHALLENGES AND ETHICS, LOOKING AHEAD TO QUANTUM HORIZONS

Data scarcity is an impediment to Engineering Dataset Creation and trust is diminished due to black-box models impacting Critical EEE. Biases that are present within the dataset can lead to greater risk of failure. The edge requirements for YOLO will require pruning while Hybrid solutions can be configured but are compute-intensive. Ethical considerations include the need to create a fair and equitable training dataset for all countries providing infrastructure. Quantum ML will potentially provide solutions to the multipliers of buffer bottlenecks, at a speed of 100 times+ more than prior algorithms ([6]), as well as providing a greater expanse of explainable hybrid ks and coupling with physics-based models to meet the twin solutions of 2030. The scaling of smart cities aligned to SDGs will include multimodal solutions (visual), vibro + markerless depth.

VI. SYNTHESIS AND ROADMAP: ML AS ENGINEERING'S CATALYST

The implementation of machine learning (ML) has significantly accelerated the shift from empirical to data-driven practices within the engineering field and facilitated a Return on Investment (ROI) between 20 to 50 percent through the hybridization of technologies, including Y-MaskNet, which provides a resilient approach to climate-related threats and hazards; furthermore, the integration of mechanical maintenance technologies, civil monitoring systems, electrical engineering and electronics (EEE) alerts, environmental control and monitoring systems (ECMS), and computer simulation engineering (CSE) will help to ensure that ML is utilized in an ethical and equitable manner as we develop ML-enabled engineering pipelines in the future. Roadmap for ML: Pilots across disciplines; Data from multiple sources available through open source; Development of quantum computing technology. Let us embrace machine learning to create a future filled with sustainable and responsive innovations based on predictive capabilities.

VII. CONCLUSION

The goal of this article is to show how Machine Learning will change every type of Engineering. We show that Hybrid Techniques like Y-MaskNet give us more accuracy and speed, improving several Engineering Fields by 15%-25%. We have validated this research with a data base of 1,200 images which have shown that the Y-MaskNet Hybrid Technique reduces Mechanical Downtime by 25% and produces 96.5% Intersection over Union (IoU) for Structural Health Monitoring (SHM) and cuts Erroneous Electric Engineering Faults (EEE) with 98.99% accuracy. In addition, it has reduced the amount of wasted resources used in Environmental Civil Engineering (ECE) by 20% and it has made Civil Engineering (CSE) Twin Spatial Transformation 100 times faster. This shows that Machine Learning has the potential to link different types of Engineering together and allow all Engineers to produce resilient/sustainable solutions in response to the anticipated global economic pressures of $3-5 Trillion. Data Sparsity and Biases can be improved through the use of Machine Learning, Ethical and Quantum Futures, and Creating a Culture of Collaborative Work among the various Disciplines. We have created an example of our work through the Calibrated Pipelines and Open Pilots Calls. Engineering can play a large role as the Catalyst of the Predictive Ingenuity of the Equitable Tomorrows.

REFERENCES

[1] S. Arjapure and D. R. Kalbande, "Deep Learning Model for Pothole Detection and Area Computation," in *Proc. 2021 Int. Conf. Commun. Inf. Comput. Technol. (ICCICT)*, 2021. Available: https://www.researchgate.net/publication/353860159_Deep_Learning_Model_for_Pothole_Detection_and_Area_Computation

[2] S.-S. Park, V.-T. Tran, and D.-E. Lee, "Application of Various YOLO Models for Computer Vision-Based Real-Time Pothole Detection," *Appl. Sci.*, vol. 11, no. 23, art. 11229, 2021. DOI: 10.3390/app112311229. Available: https://www.mdpi.com/2076-3417/11/23/11229

[3] Ruseruka et al., "Augmenting Roadway Safety with Machine Learning and Deep Learning: Pothole Detection and Dimension Estimation Using In-Vehicle Technologies," *Mach. Learn. Appl.*, vol. 16,art.100547, 2024. Available: https://www.sciencedirect.com/science/article/pii/S2666827024000239

[4] C.-B. Lin and Y. Liu, "Research on Potholes Detection Based on Improved Mask R-CNN Algorithms," Dept. Inf. Commun. Eng., Chaoyang Univ. Technol., conf. paper, 2024. Available: https://ir.lib.cyut.edu.tw/bitstream/310901800/42097/2/DCC-Research%2Bon%2BPotholes%2BDetection%2BBased%2Bon%2BImproved%2BMask%2BRCNN%2BAlgorithms%2B%281%29.pdf

[5] Y. Tan and X. Li, "UAV Photogrammetry-Based 3D Road Distress Detection," *ISPRS Int. J. Geo-Inf.*, vol. 8, no. 9, art. 409, 2019. Available: https://www.mdpi.com/2220-9964/8/9/409

[6] Wang, H. Zhu, Y. Xu, and K. Liu, "Robust Video-Based Pothole Detection and Area Estimation for Intelligent Vehicles with Depth Map and Kalman Smoothing," arXiv:2505.21049, 2025. Available: https://arxiv.org/abs/2505.21049

[7] T. Tocci, L. Capponi, and G. Rossi, "ArUco Marker-Based Displacement Measurement Technique: Uncertainty Analysis," *Eng. Res. Express*, vol. 3, no. 3, 2021. DOI: 10.1088/2631-8695/ac1fc7. Available: https://www.researchgate.net/publication/354036017_ArUco_marker-based_displacement_measurement_technique_Uncertainty_analysis

[8] P. Oščádal et al., "Improved Pose Estimation of ArUco Tags Using a Novel 3D Placement Strategy," *Sensors*, vol. 20, no. 17, art. 4825, 2020. Available: https://www.mdpi.com/1424-8220/20/17/4825

[9] Khamkaew et al., "Pothole Detection and Dimension Estimation via Image Transformation and Scaling with Thai Road Data Integration," *ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci.*, vol. X-4/W7-2025, pp. 75-81, 2025. DOI: 10.5194/isprs-annals-X-4-W7-2025-75-2025. Available: https://isprs-annals.copernicus.org/articles/X-4-W7-2025/75/2025/isprs-annals-X-4-W7-2025-75-2025.html

[10] Li et al., "Rural Road Surface Distress Detection Algorithm Based on Mask R-CNN with Data Augmentation," *Front. Built Environ.*, 2025. Available: https://www.frontiersin.org/journals/built-environment/articles/10.3389/fbuil.2025.1566979/full

[11] G. Jia et al., "Visible & Thermal Imaging and Deep Learning Based Pothole Detection and Mapping," *Mountain-Plains Consort. Tech. Rep. MPC-24-559*, 2024. Available: https://www.ugpti.org/resources/reports/downloads/mpc24-559.pdf

[12] T. Guan, J. Cai, Y. Wang, W. Yang, X. Chang, and Y. Han, "Pavement Pothole Detection System Based on Deep Learning and Binocular Vision," *J. Traffic Transp. Eng. (Eng. Ed.)*, vol. 12, no. 4, pp. 1100-1123, 2025. Available: https://www.sciencedirect.com/science/article/pii/S2095756425001126

[13] DINO-YOLO: A Hybrid Architecture for Data-Efficient Object Detection, arXiv:2510.25140, Oct. 2025. Available: https://arxiv.org/pdf/2510.25140

[14] A Hybrid Framework for Object Detection and Segmentation in Autonomous Vehicles, *J. Theor. Appl. Inf. Technol.*, vol. 103, no. 6, pp. 1-15, Mar. 2025. Available: https://www.jatit.org/volumes/Vol103No6/30Vol103No6.pdf

[15] A Decade of You Only Look Once (YOLO) for Object Detection, *IEEE Access*, Nov. 2025. Available: https://ieeexplore.ieee.org/iel8/6287639/10820123/11237046.pdf

[16] Track Intrusion Detection and Track Integrity Evaluation Using YOLO-RCNN, UTRGV Rep., Sep. 2025. Available: https://www.utrgv.edu/railwaysafety/_files/documents/reports/o7cy24_track-intrusion-detection-and-track-integrity-evaluation_year-2_091925.pdf

[17] Accuracy of Hybrid Models for Automatic Road Damage Evaluation, *Civ. Eng. Archit.*, May 2024. Available: https://www.hrpub.org/download/20240530/CEA12-14836831.pdf

[18] Design of a Generic Fault Diagnosis Model for Electrical Distribution Systems, *IEEE Trans. Power Deliv.*, Sep. 2025. Available: https://ieeexplore.ieee.org/iel8/6287639/10820123/11142777.pdf

[19] Sustainable Deep Learning-Based Fault Detection for Next-Generation Power Systems, *IAENG Int. J. Comput. Sci.*, 2025. Available: https://www.iaeng.org/IJCS/issues_v52/issue_7/IJCS_52_7_39.pdf

[20] AI-Powered Machine Learning Approaches for Fault Diagnosis in Industrial Pumps, arXiv:2508.15550, Aug. 2025. Available: https://arxi v.org/pdf/2508.15550

BIOGRAPHY:

Sindhu Patchigolla is a PhD scholar in Computer Science specializing in AI and machine learning. She has experience in data analysis, model development, and applied research. Her current PhD research focuses on developing intelligent systems for real-time prediction and automation.