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Thesis Proposal

Solar Panel Fault Detection Using Computer Vision

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Abstract

As solar panel installations on residential properties increase, the demand for efficient maintenance and fault detection is expected to grow. Common solar panel defects, such as micro-cracks, dust accumulation, and delamination, can significantly impact power output and long-term performance. However, current datasets for solar panel fault detection are limited to less than 1000 images, hindering the development of robust detection models. This research proposes to address this gap by expanding the dataset through AI-generated synthetic images and manual collection of real-world solar panel defects. A two-stage pipeline is proposed, comprising an object detection model (YOLOv11) followed by a high-precision classifier (ConvNeXt) to enhance detection accuracy for small defects. The hypothesis is that this approach will outperform single-stage object detection models by leveraging targeted classification of defect regions. If successful, the developed pipeline could be adapted for commercial applications in solar panel maintenance and inspection.

Glossary

Abbreviation	Full Form / Description
AD	Anno Domini
AGX	Advanced Graphics Accelerator
AP	Average Precision
CAGR	Compound Annual Growth Rate
CAM	Class Activation Mapping
CNN	Convolutional Neural Network
COCO	Common Objects in Context
CVAT	Computer Vision Annotation Tool
DETR	Detection Transformer
DINO	Denoising Diffusion Probabilistic Model
DLA	Deep Learning Accelerator
EL	Electroluminescence
FLOP	Floating Point Operation
FP	False Positive
FP (Deformable)	False Positive in Deformable Attention Transformers
FPR	False Positive Rate
FPS	Frames Per Second
GB	Gigabyte
GPU	Graphics Processing Unit
GW	Gigawatt
ID	Identification
IR	Infrared
LPIPS	Learned Perceptual Image Patch Similarity
MMD	Maximum Mean Discrepancy
MP	Megapixel
NAS	Neural Architecture Search
NZD	New Zealand Dollar
OF	Optical Flow
PERC	Passivated Emitter Rear Contact
PR	Performance Ratio
PR (Analysis)	Performance Ratio Analysis
PSA	Polarized Self Attention
PV	Photovoltaic
PVEL	PV Evolution Labs
RGB	Red, Green, Blue
RT	Real-Time
RTX	Ray Tracing Texel eXtreme
SEDD	Self-Supervised Efficient Defect Detector
SPF	Solar Panel Fault
TB	Terabyte
TW	Terawatt
UK	United Kingdom
US	United States

USB	Universal Serial Bus
USD	United States Dollar
XFDDS	Explainable Fault Detection and Diagnosis System
XL	Extra Large
YOLO	You Only Look Once

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1. Introduction

1.1 Background

The solar photovoltaic (PV) industry stands at a pivotal moment of unprecedented growth, yet it faces significant challenges related to panel defects and detection methodologies. This background examines the market trajectory, economic implications of panel defects, current detection limitations, and emerging technological solutions.

Global Solar PV Market Growth and Economic Projections

The global solar photovoltaic market is experiencing remarkable expansion, with projections indicating substantial growth through 2028. According to Fortune Business Insights, the global solar PV market is expected to reach USD 1,000.92 billion by 2028, exhibiting an impressive CAGR of 25.9% during the forecast period[1] . This represents a dramatic increase from its 2020 valuation of USD 154.47 billion[1]. Alternative market analyses provide slightly different but still optimistic projections, with some estimating the broader solar power market to reach USD 293.18 billion by 2028, growing at a CAGR of 6.9%[2], [3].

The solar energy sector's growth trajectory is driven by multiple factors.

Key Market Drivers

The explosive expansion of solar energy adoption is fueled by several interconnected factors. Declining costs of solar PV technology have made implementation increasingly economical, with solar PV module prices falling nearly 50% in 2023 alone [4]. Government policies supporting renewable energy adoption across more than 130 countries have created favorable regulatory environments[4]. Additionally, growing environmental concerns and the urgent need for decarbonization have accelerated investment in solar infrastructure[4], [5].

China maintains dominance in the global solar manufacturing landscape, controlling 80-95% of global supply chains. However, other major markets including the United States, European Union, India, and Brazil are rapidly increasing installations. By 2028, wind and solar PV combined are projected to double their share of global electricity generation to 25%, with solar PV surpassing nuclear electricity production by 2026[4]

Installation Projections

Solar PV installations are expected to more than double between 2022 and 2028[4]. By the end of 2024, the global solar PV supply is anticipated to reach 1,100 GW, three times the current demand forecast. Cumulative solar PV capacity is expected to surpass 3.5 terawatts by 2027, representing an increase of over 2.3 terawatts compared to 2022[6]. This massive expansion will require significant investments, with Navigant Research estimating approximately US$2035.6 billion in revenue for the industry globally between 2019 and 2028 [7].

Impact of Panel Defects on Performance and Economics

Despite the industry's impressive growth, solar PV systems face significant challenges related to panel defects that compromise efficiency and economic returns.

Types and Prevalence of Panel Defects

Solar panels commonly experience several types of defects that impact performance:

1. **Hot spots**: Areas on panels that become overloaded and overheat, primarily caused by badly-soldered connections or structural defects in solar cells[8]. These can ultimately lead to short-circuits, reducing both performance and lifespan of PV panels [8].

2. **Microcracks**: Nearly imperceptible microscopic tears in solar cells that can occur during production, shipping, or installation. While they may not cause immediate production loss, they can grow over time due to thermal tension or weather conditions, eventually leading to significant damage and power reduction[8].

3. **Cell cracks**: Caused by excessive thermal and mechanical stress from manufacturing defects, environmental conditions (temperature fluctuations, freeze-thaw cycles, wind, snow, hail), or physical damage during transportation, installation or maintenance[9].

Quantifiable Impact on Power Output

The impact of defects on solar panel performance has been extensively documented through empirical research:

1. **Hot spot impact**: PV modules with hot-spotted solar cells experience a progressive reduction in power output as the number of hot spots increases. Hot spots occur when cells within the module operate at different temperatures, often due to shading, manufacturing defects, or cell mismatches. This thermal disparity can result in localized heating, causing certain cells to consume power instead of generating it. As the number of hot spots increases, the overall module efficiency declines, affecting both individual cells and entire strings of interconnected modules. Over time, this degradation can escalate, leading to severe performance losses and potential long-term damage to the PV system. Consequently, early detection and mitigation of hot spots are crucial to maintaining optimal power output and ensuring the longevity of solar installations. [10].

2. **Crack size and orientation effects**: Diagonal cracks affecting a single solar cell reduce power output by 0.35-0.44%, while the same type of crack affecting five solar cells can cause power reductions of 2.97-5.37%. Parallel-to-busbar cracks demonstrate similar progressive impacts, with one affected cell causing 0.75-0.97% power reduction, while three to four affected cells result in 2.39-3.0% and 3.67-4.55% power losses respectively[11].

3. **Cumulative effect**: Problems with panels can result in production losses of up to 20%, as a poorly performing panel affects the production of an entire string of panels[8]. Larger cracks can lead to drastic decreases in output power approaching 60% in severe cases[12].

4. **Degradation over time**: A recent analysis of PV modules installed in Jordan found that severe cell cracks caused power losses as high as 9% in monocrystalline PERC modules after just four months of field exposure[9]. This highlights how defects can rapidly compromise system performance.

Emerging Trends and Technological Challenges

Panel Design Evolution and Associated Risks

Recent trends in PV module design could significantly increase cell crack susceptibility. Manufacturing shifts toward larger format, higher-powered PV modules may elevate cracking risks because:

1. They contain larger silicon wafers subjected to pressures over greater surface areas
2. The modules may experience more deflection during high wind and snow loads
3. Some manufacturers are using thinner glass materials to reduce weight, potentially compromising durability [13].

Geographic and Environmental Factors

Geographic location plays a significant role in defect occurrence and impact. Research analyzing 2,580 polycrystalline silicon PV modules across the UK found that 92.15% of PV modules affected by hot-spotted PV strings were in northern regions, where low temperatures, heavy snow, and hoarfrost are more significant[10]. Conversely, 82.41% of modules affected by only one hot-spotted solar cell were in coastal areas, suggesting lower risks for multiple hot-spotted cells in these regions compared to central and colder locations[10].

Research Needs and Future Directions

The growing solar PV market requires improved methodologies for defect detection and mitigation. Several critical research areas emerge:

1. **Development of standardized testing protocols**: Current research demonstrates wide variations in how defects impact performance, necessitating standardized approaches to quantify and predict degradation[11], [12]
2. **Advanced imaging and detection technologies**: Electroluminescence (EL) imaging has proven valuable for identifying cracks and predicting their impact, but more sophisticated and automated detection systems are needed[11], [12].
3. **Performance ratio analysis**: Studies examining the performance ratio (PR) of affected modules show significant reductions due to hot spots, highlighting the need for monitoring systems that can detect performance deviations early[10].

4. **Mitigation strategies**: Research into module designs and materials that minimize crack propagation and hot spot formation remains essential[9].

The solar PV market is poised for extraordinary growth through 2028, with projections indicating a multi-fold increase in capacity and economic value. However, panel defects present significant challenges to realizing the full potential of this expansion. Microcracks, hot spots, and cell damage can substantially reduce power output, with impacts ranging from less than 1% for minor defects to over 20% for severe cases. As the industry continues its rapid growth trajectory, investment in defect detection, quality control, and mitigation strategies will become increasingly critical to ensuring the economic viability and sustainability of solar PV installations worldwide.

1.2 Aim

The global solar photovoltaic (PV) sector is expanding at a compound annual growth rate exceeding 20 % and is projected to surpass 3 TW of installed capacity before 2030 [14]. With this rapid deployment, even seemingly minor faults— including micro-cracks, hot-spots, delamination, and snow or dust accretion— can induce annual energy-yield losses of 3–8 %, translating to millions of dollars for utility-scale sites [15], [16]. Small defects (< 25 pixels in typical inspection imagery) are particularly problematic: they escape thermographic walk-downs and elude the receptive fields of many convolutional detectors yet often act as nucleation points for larger failures that accelerate module degradation[17], [18].

Academic data resources remain insufficient for this fine-grained regime. Flagship visible-light datasets such as SPF-Net (885 annotated panels) and EL-based PVEL-AD (≈36 k cells) contain < 15 % samples with micro-defects, while rare categories— electrical arcing traces (≈ 3.7 %) or localized snow coverage (≈ 5.1 %)— are severely under-represented[19], [20]. Such skew limits the statistical power of model evaluation and fosters class-imbalance bias that inflates false-negative rates for the very faults most likely to propagate.

Compounding the data gap, PV arrays operate under highly heterogeneous environmental conditions. Illumination levels can span 50–100 000 lx, panels may be partially shaded or occluded by mounting hardware, and ambient temperatures on rooftops can oscillate from −10 °C to > 60 °C in a single day [21], [22]. These factors perturb image appearance, shifting feature distributions and stressing the domain-robustness of learned detectors. Consequently, empirical understanding of how data composition and environmental variability jointly influence small-defect detection performance remains fragmentary.

Accordingly, this study sets out to **systematically quantify** the relationships between dataset composition, operational conditions, and detection accuracy for ≤ 25-pixel PV defects. By analyzing precision-recall curves, and false-positive escalations across diverse defect typologies and field scenarios, the research will generate evidence-based insights that advance the reliability of automated PV inspection and contribute to the broader literature on fine-grained fault analytics—without presupposing any specific algorithmic solution.

2. Literature Review

2.1 Evolution of CNN Architectures in PV Inspection

Convolutional Neural Networks (CNNs) have dominated photovoltaic defect detection since their adaptation from general computer vision tasks. The foundational work by Huang et al. demonstrated YOLOv5's effectiveness with 95.5% mAP for macro-defects (>100 pixels), though revealing an 18% recall drop for sub-50-pixel anomalies due to spatial pyramid down sampling[23]. Subsequent improvements incorporated coordinate attention mechanisms, boosting mAP to 95.5% while maintaining 1120 FPS on GPUs through weighted bidirectional feature fusion[23], [24].

ResNet50 emerged as a laboratory benchmark with 97.06% accuracy under control conditions, but field deployments exposed critical limitations - a 30% recall decline for ≤25-pixel defects in aerial imagery due to fixed receptive fields[23], [25]. This scale sensitivity became a focal point for architectural innovations, with MobileNetV3 achieving 95% accuracy in edge deployments through inverted residuals and hard-swish activations, albeit sacrificing global context integration[24], [26].

Hybrid architectures marked a significant evolution, as demonstrated by Rudro et al.'s SPF-Net combining U-Net segmentation with InceptionV3 classification [23]. While achieving 94.35% test accuracy, the model struggled with partial occlusion (22% recall drop), highlighting the need for improved contextual understanding[20], [27]. Ledmaoui et al.'s VGG16 implementation further illustrated CNN limitations, achieving 91.46% accuracy across six fault classes but failing to localize defects occupying <0.05% of high-resolution frames[28].

2.2 Transformer Revolution and Attention Mechanisms

Vision Transformers (ViTs) introduced paradigm-shifting capabilities through self-attention mechanisms. The Swin Transformer V3's shifted-window attention improved small-defect recall by 15% versus CNNs by establishing long-range dependencies in 4K drone imagery[29], [30]. Lang & Lv's YOLO-PSA architecture exemplified hybrid potential through polarized self-attention, boosting mAP@50 by 17.2% via spatial-semantic decoupling[31].

Real-time implementations like RT-DETR addressed computational concerns through deformable attention, achieving 64.7% mAP@0.5 while eliminating non-maximum suppression - critical for drone-based inspections requiring <30ms latency[32], [33]. Dwivedi et al.'s pure ViT model surpassed CNNs in drone inspections (>97% accuracy), validating transformers' superiority in global feature extraction[27], [34]. However, the 200+ GFLOPS requirement of SwinV3 versus YOLOv5's 12.9 GFLOPS highlighted persistent efficiency challenges[23], [29].

2.3 Hybrid Architectures: Bridging the Performance Gap

Recent architecture strategically combines CNN efficiency with transformer precision. Di Tommaso et al.'s YOLOv3-IR demonstrated multi-spectral fusion, achieving 98% AP@0.5 through early integration of visible/thermal inputs [26]. The YOLOv11 + ConvNeXt pipeline reduced false positives by 34% in desert installations through dynamic multi-scale processing, though introducing 18-22ms latency overhead[24], [35].

Zhang et al.'s NAS-optimized CNN achieved 91.74% accuracy with 1.85M parameters through automated kernel selection, while maintaining compatibility with TensorRT quantization for edge deployment[24]. Comparative studies revealed transformer-CNN hybrids outperform pure architectures in mAP@50-95 (95.7% vs 89.3%) but require careful latency management through techniques like DLA offloading[32].

2.4 Data Augmentation and Synthetic Generation

Dataset limitations persist as a critical barrier, with PVEL-AD's 36,543 EL images containing <15% small-defect samples[31]. CycleGAN-based domain adaptation emerged as a key solution, improving model robustness by 19% through realistic snow pattern synthesis. ControlNet's structure-preserving generation proved particularly effective for electrical damage defects, boosting recall by 27% at 30% synthetic ratios[31].

Optimal augmentation strategies show environment-specific characteristics:

- 20% synthetic: +9.3% mAP in desert installations
- 30% synthetic: +15% recall in temperate zones
- 40% synthetic: -6.7% performance due to domain shift.

Recent innovations like physics-guided Stable Diffusion XL reduced the reality gap by 38% through finite element-based thermal profile generation[24]. However, Korkmaz et al. cautioned against excessive augmentation (>35%), demonstrating 9.2% false positives from synthetic artifacts in field trials.

2.5 Edge Deployment and Computational Optimization

Edge deployment of PV defect detection systems requires balancing computational efficiency with detection accuracy. NVIDIA Jetson Nano platforms demonstrate this trade-off, achieving 4.91ms/inference for YOLOv11-n at FP16 precision using TensorRT quantization, which reduces model size by 58% (10.5MB → 5.6MB) while maintaining 84.1% recall@50[36], [37]. However, latency variability remains a critical challenge, with Jetson Nano exhibiting 23% inference time variance across operating temperatures (-10°C to 50°C) [36]. Comparative benchmarks reveal Coral USB accelerators achieve 199.5 FPS on MobileNetV2 versus Jetson's 45.2 FPS, though limited to 4MB model sizes- a constraint that excludes transformer-based architectures like SwinV3-Tiny (22.3ms latency)[38], [39].

The choice of quantization strategy significantly impacts performance. TensorRT INT8 calibration reduces YOLOv11-n's memory footprint by 58% while limiting mAP drops to <3%, making it viable for drone-mounted deployments[37], [40]. However, INT8 quantization introduces accuracy trade-offs for rare defect classes- electrical damage detection precision drops 8.7% compared to FP16, highlighting the need for adaptive quantization thresholds[41]. DLA offloading addresses these limitations by allocating YOLOv11 inference to Jetson's dedicated Deep Learning Accelerator cores, achieving consistent 4.91ms latency even under thermal stress[37], [42].

Multimodal fusion strategies present new optimization frontiers. Chen et al.'s acoustic-thermal-visual pipeline synchronizes microphone arrays with IR cameras, achieving 98.5% defect prediction accuracy[31]. This approach eliminates 37% of false positives caused by shadow artifacts in RGB-only systems but requires <10cm sensor proximity-a challenging constraint for utility-scale PV farms spanning hectares[31]. Hybrid architectures like YOLOv11 + ConvNeXt demonstrate better scalability, reducing false positives by 34% in desert installations through dynamic multi-scale processing, albeit with 18–22ms latency overhead [43], [44].

Recent studies highlight the growing efficacy of integrating thermal imaging with RGB data to improve the reliability of solar panel fault detection—especially for identifying faults such as hotspots, cracks, or delamination, which may not be visible in standard visual spectra. Thermal imaging enables the detection of temperature anomalies that signal underlying issues like internal resistance buildup or bypass diode malfunction, which often precede visible surface damage. For instance, Di Tommaso et al. employed a UAV-based dual-modality setup using infrared (IR) and RGB imaging, significantly enhancing the detection accuracy of latent photovoltaic faults compared to single-sensor approaches [25]. Similarly, Chen et al. integrated acoustic, thermal, and visual data into a multimodal pipeline, achieving a 98.5% accuracy in fault prediction while reducing shadow-induced false positives by 37% [31]. Yalçın (2025) also demonstrated that thermal-based inspection increased energy efficiency evaluations by revealing cell-level hotspots not detectable in RGB images alone [21]. In another study, Shafiei et al. (2023) noted that combining thermal and RGB modalities within deep learning frameworks improved classification confidence and robustness under variable illumination conditions [42]. These findings are supported by broader reviews of deep learning applications in PV inspection, which recommend multi-modal fusion as a means to compensate for occlusions, illumination shifts, and defect types invisible to RGB-only models [33]. Overall, augmenting RGB imagery with thermal data provides a more comprehensive feature space for detecting subtle or early-stage defects and is thus a critical direction for future solar fault diagnostics.

2.6 Research Gaps and Future Directions

Four critical gaps persist in PV defect detection research:

1. Multi-modal Benchmarking: Current studies like SPF-Net[45] and PVEL-AD [46] focus on single modalities (EL/visible/IR), neglecting fused datasets that reflect real-world inspection conditions. Chen's acoustic-thermal fusion [31] achieves 98.5% accuracy but lacks integration with electroluminescence data, missing opportunities to detect latent cracks through multi-spectral analysis[47].

2. Self-Supervised Learning: The unlabeled EL-10k dataset remains underutilized-contrastive pretraining reduces labeling costs by 40% but still lags supervised methods by 6.2% mAP[48]. Techniques like SEDD (Self-Supervised Efficient Defect Detector) show promise, achieving 82.3% recall@50 with only 1,000 labeled images, yet require architectural innovations to close the performance gap[49].

3. Dynamic Environments: Only 12% of studies test models under variable illumination (50–100,000 lux) and particulate loads (5–20g/m^2 dust), despite field data showing 34% performance variance[50], [51]. The PVEL-AD dataset's controlled acquisition conditions (static lighting, clean panels) poorly represent desert installations where daily dust accumulation reduces mAP by 19%[52].

4. Explainability: Transformer detectors lack interpretability frameworks comparable to CNN-based XFDDS systems, which provide physical irradiance models for 89% of predictions[53]. While Grad-CAM visualizations explain YOLOv5's attention patterns, they fail to quantify how defect geometry influences classification confidence-a critical requirement for regulatory compliance in utility-scale deployments[54].

Emerging techniques like neural architecture research (NAS) and physics-guided synthesis address these gaps. Zhang et al.'s NAS-optimized model achieves 91.74% accuracy with 1.85M parameters through automated kernel size selection, reducing FLOPs by 34% compared to manual designs[55]. Stable Diffusion XL introduces finite element simulation into synthetic defect generation, cutting the reality gap (measured by Fréchet Inception Distance) by 38% versus purely data-driven GANs [56], [57]. Future work must integrate these advances into unified pipelines that balance accuracy, explainability, and edge deployability.

2.7 Conclusions

This review synthesizes 30 studies to establish hybrid CNN-transformer architectures with ≤30% synthetic augmentation as the state-of-the-art for PV defect detection, achieving 95.7% mAP@50-95 in controlled environments. Key findings include:

- Model Performance: Swin Transformer V3 improves small-defect recall by 15% over CNNs but demands 200+ GFLOPS, while YOLOv11 + ConvNeXt reduces false positives by 34% with manageable 18ms latency overhead[44], [58].
- Edge Optimization: TensorRT INT8 quantization enables ≤100ms inference on Jetson Nano, though Coral USB accelerators achieve 4.42× faster FPS for lightweight models[37], [39].
- Data Augmentation: CycleGAN and ControlNet synthetics boost rare defect recall by 12–15% at 30% ratios, but excessive augmentation (>35%) introduces domain shifts that degrade mAP by 6.7%[57], [59].

The field remains constrained by fragmented benchmarks and insufficient real-world testing. Systematic evaluation of emerging architectures like RT-DETR and DINO across diverse PV technologies and environmental conditions is urgently needed. Future research should prioritize physics-informed synthetic data, multi-modal sensor fusion, and quantization-aware training to bridge the gap between laboratory accuracy and field reliability.

3. Proposed Research

3.1 Research Gap

3.1.1 Data Scarcity for Small Defects

Existing datasets like SPF-Net (885 images) and PVEL-AD (36,543 EL images) exhibit critical imbalances, with ≤25px defects representing only 14% of annotated instances[20], [36]. Rare defect types such as electrical damage (3.7% prevalence) and snow coverage (5.1%) are severely underrepresented, limiting model generalizability across operational environments[31], [36]. For instance, PVEL-AD contains only 9 corner defects and 5 scratch instances in its training set, while SPF-Net focuses primarily on macro-defects like cracks and delamination[20], [36].

Proposed Solution: Integrate 300–500 synthetic images via CycleGAN (domain adaptation), ControlNet (structural consistency), and Stable Diffusion XL (text-to-image synthesis) to augment underrepresented classes. Preliminary tests show synthetic data improves small-defect recall by 12–15% at 30% augmentation ratios[20], [36], [60].

3.1.2 Benchmark Fragmentation and Model Performance

While transformer models like Swin V3 (77.9% mAP@0.5) and RT-DETR (64.7% mAP@0.5) demonstrate 12–15% recall improvements for small defects over CNNs, their computational demands (≥200 GFLOPS) hinder real-time deployment[29], [61], [62]. Current literature lacks standardized comparisons between:

- Single-stage detectors (YOLOv5, YOLOv11)
- Two-stage pipelines (YOLOv11 + ConvNeXt)
- Transformer hybrids (DINO, SwinV3-YOLO).

Proposed Solution: Implement unified evaluation metrics:

Metric	Definition
mAP@0.5	Mean AP at IoU=0.5
Recall@50	Detection rate for top 50 proposals
Latency	Inference time on Jetson Nano (ms)

Benchmarks will assess performance under 20%, 30%, 40% synthetic data ratios, addressing reproducibility gaps in prior works[23], [31], [37].

3.1.3 Synthetic Data and Domain Shift Risks

Excessive synthetic augmentation (>35%) introduces domain shifts, degrading model robustness by 6.7% mAP@0.5 in cross-dataset testing[23], [60]. For example, CycleGAN-generated snow patterns caused 9.2% false positives when applied to desert PV farms in field trials[20], [36].

Proposed Solution: Conduct ablation studies measuring:

1. **Feature distribution divergence** using Maximum Mean Discrepancy (MMD)
2. **Small defect recall stability** across synthetic ratios (20/30/40%)
3. **F1-score variance** under illumination changes (50–100,000 lux).

3.1.4 Unexplored Hybrid Architectures

Current studies in solar panel fault detection focus on pure CNNs or transformers, neglecting hybrid potential:

- **YOLO-PSA**: Polarized self-attention boosts mAP@50 by 17.2% but lacks multi-scale fusion[31].
- **Bearing-DETR**: Combines deformable attention with MobileNet blocks, reducing FLOPs by 34%[32].

Proposed Direction: Develop YOLOv11-ConvNeXt with:

1. **Dynamic head**: Adjusts receptive fields for 25–100px defects
2. **Cross-attention fusion**: Integrates YOLO's C3 blocks with ConvNeXt's inverted bottlenecks
3. **Quantization-aware training**: Maintains INT8 accuracy during edge deployment.

This systematic gap analysis identifies critical barriers to small-defect detection while proposing actionable solutions grounded in recent advances [63], [64], [65].

3.2 Research Questions

3.2.1 Data Augmentation and Defect Detection

Key Question: *How do synthetic data ratios (20%, 30%, 40%) impact recall and precision for small defects (≤25 pixels)?*

- **Small-defect recall degradation**: SPF-Net reports 22% recall drops for defects ≤25 pixels under real-only data[66], [67].
- **Synthetic augmentation trade-offs**:

- **20% synthetic**: Improves mAP@0.5 by 9.3% but risks underrepresentation of rare defects (electrical damage, snow coverage)[68], [69].
- **30% synthetic**: Optimal balance, boosting recall@50 by 15% while maintaining domain alignment[70], [71].
- **40% synthetic**: Introduces feature distribution divergence (MMD >0.4), reducing mAP@0.5 by 6.7%[72], [73].

- **Proposed Methodology**:
  - Generate 300–500 synthetic images via CycleGAN (domain adaptation) and ControlNet (structural consistency)[68], [71].

    While the exact quantity of synthetic images needed for optimal performance depends on the dataset characteristics and model complexity, generating **300–500 synthetic images** is considered sufficient for this study due to the balance it provides between **augmentation impact and domain overfitting risk**. Prior research on defect detection in photovoltaic (PV) systems using deep learning shows that **small-scale augmentation (≤40%)** can significantly improve recall for underrepresented defect types without introducing excessive domain shift, particularly when using advanced generative models such as **CycleGAN** and **ControlNet** [74], [75]. Specifically, studies by Zhang et al. and Xiao et al. observed that models trained with approximately 25–35% synthetic data (300–500 images in datasets with ~1,000–2,000 total samples) demonstrated improved generalization and higher recall@50 for small or rare defects [74], [75]. Additionally, generating more than 500 synthetic images tends to introduce **distributional divergence**, as seen when MMD exceeds 0.4, leading to reduced precision and unstable training performance [76]. Therefore, capping synthetic data generation within the 300–500 range offers a **controlled enhancement**, improving performance metrics like mAP@0.5 and F1-score, while minimizing risks associated with over-reliance on synthetic distributions.

- Measure precision-recall curves using F1-score harmonic mean across ratios[70], [73].

3.2.2 Model Performance Analysis

Key Question: *Which architecture balances accuracy, recall, and latency under real/synthetic data?*

- **YOLOv11**: Achieves 95.7% mAP@50-95 with 12.9% fewer parameters than YOLOv5 but struggles with ≤25px defects (recall@50=68.5%)[63], [77].
- **Swin Transformer V3**: Improves small-defect recall by 15% via shifted-window attention but requires 200+ GFLOPS[67], [72].
- **RT-DETR**: Optimized for real-time use (32.7ms latency) but suffers 8.2% mAP drop vs. YOLOv11 under synthetic data[72], [78].
- **ConvNeXt**: Delivers 87.4% ImageNet-1k accuracy with 34% fewer FLOPs than SwinV3 but lacks detection capabilities [71], [73].
- **Proposed Methodology**:
    a. Benchmark models on PVEL-AD (36k EL images) using mAP@0.5, recall@50, and FPS[64], [66].
    b. Validate generalizability via cross-dataset testing on SPF-Net (885 images)[66], [67].

3.2.3 Pipeline Optimization

Key Question: *How does YOLOv11 + ConvNeXt compare to single-stage YOLOv11?*

- **Two-stage advantages**:
    - Reduces false positives by 34% via ConvNeXt's bilinear attention[73], [78].
    - Improves ≤25px defect recall by 12% (72.1% → 84.1%)[63], [78].
- **Single-stage advantages**:
    - Lower latency (4.91ms vs. 22.3ms on Jetson Nano)[71], [72].

- Simpler deployment with 58% smaller footprint after TensorRT INT8 quantization[71], [72].

- **Proposed Methodology**:
  - Implement dynamic head scaling in YOLOv11 for multi-scale proposals[63], [78].
  - Integrate cross-attention fusion between YOLO's C3 blocks and ConvNeXt's inverted bottlenecks[73], [78].

3.2.4 Deployment Analysis

Key Question: *Can the optimized pipeline achieve ≥85% recall at ≤100ms on Jetson Nano?*

- **Baseline performance**:
  - YOLOv11-n: 84.1% recall@50 at 4.91ms (FP16)[71], [72].
  - ConvNeXt-Tiny: 87.4% accuracy at 18.2ms[73], [78].
- **Optimization strategies**:
  - **TensorRT INT8**: Reduces model size by 58% (10.5MB → 5.6MB) with <3% recall loss[71], [72].
  - **DLA offloading**: Allocates YOLOv11 to Jetson's Deep Learning Accelerator, achieving 4.91ms/inference [71], [72].
- **Proposed Methodology**:
  - Validate latency-recall trade-offs using **NVIDIA Nsight Systems** profiler[71], [72].
  - Test robustness under environmental variations (50–100,000 lux illumination, 5–20g/m^2 dust)[66], [71].

Synthesis: These questions systematically address critical gaps in small-defect detection, leveraging hybrid architectures and synthetic data to optimize for accuracy, speed, and deployability.

3.3 Hypotheses

This study proposes three key hypotheses to evaluate the impact of synthetic data augmentation and model architecture on solar panel defect detection.

First, it is hypothesized that adding around **30% synthetic images** to the training data will significantly improve the **recall and precision** for small defects (≤25 pixels), without causing domain shift or overfitting. This ratio is expected to offer the best trade-off between performance gain and feature consistency.

Second, the study assumes that **transformer-based models** (such as RT-DETR, DINO, and Swin Transformer V3) will outperform traditional **CNN-based detectors** like YOLOv11 in identifying small or subtle defects. Their global attention mechanisms are expected to improve localization and classification accuracy.

Finally, the third hypothesis suggests that a **two-stage pipeline**, combining an object detector and a separate image classifier, will provide better **defect classification performance** than a single-stage approach. This setup is expected to improve F1-score while staying within edge deployment limits (e.g., ≤100 ms latency).

Synthetic-Data Ratio Hypothesis

H1: A 30% synthetic / 70% real mix will maximize small-defect performance, yielding the highest recall @ 25 px and mAP @ 0.5 across all detectors in Experimental Set-up A, outperforming both 20% and 40% synthetic ratios.

Rationale: Prior PV-inspection work indicates that 20–40% high-fidelity synthetic injections can enhance small-object recall by 9–15%, with peak gains near 30% before domain divergence erodes accuracy [79].

Supporting evidence: Texture-divergence analyses using LPIPS and MMD metrics report a strong negative correlation ($r \approx -0.61$) between divergence > 0.4 and mAP once the synthetic share rises above 35%[80] .

Null Hypothesis: The 20%, 30%, and 40% synthetic ratios produce no statistically significant difference ($\alpha = 0.05$) in recall or mAP[80].

Two-Stage vs. One-Stage Pipeline Hypothesis

H2: The YOLOv11 + ConvNeXt two-stage pipeline in Experimental Set-up B will achieve an F1-score ≥ 0.85 on ≤ 25 px defects—at least 10% higher than single-stage YOLOv11—while maintaining ≤ 100 ms end-to-end latency on Jetson Nano after INT8 TensorRT quantization.

Rationale: YOLOv11's dynamic C3-k2 heads reduce false positives by approximately 34%, and a ConvNeXt-Tiny classifier adds around 17% precision on fine-grained PV faults, yet both remain within the 100 ms latency budget when INT8-compressed [80].

Supporting evidence: YOLOv11-n inference runs at approximately 4.9 ms; adding a ≤ 18 ms classifier sustains 30 fps streaming [81].

Null Hypothesis: The two-stage pipeline yields ≤ 5% F1 improvement or exceeds the 100 ms latency target, providing no practical benefit over single-stage YOLOv11.

Transformer Accuracy–Latency Trade-Off Hypothesis

H3: Within Experimental Set-up A, any transformer detector (RT-DETR, DINO, Swin-V3) whose latency is less than twice that of YOLOv11 will still deliver ≥ 15% higher recall @ 25 px compared with YOLOv11, confirming a favorable accuracy-latency balance for real-time PV inspection.

Rationale: Sparse deformable attention and contrastive denoising markedly boost small defect recall but add compute overhead; this hypothesis tests whether at least one transformer model meets both thresholds [82].

Supporting evidence: RT-DETR achieves 64.7% mAP with only 1.8× YOLOv11 latency, while DINO and Swin-V3 yield 18–22% and approximately 15% recall gains but incur larger FLOP footprints [31], [83].

Null Hypothesis: Every transformer detector either fails to improve small defect recall by ≥ 15% or incurs a latency penalty > 2× YOLOv11, negating its usefulness for edge deployment.

3.4 Experimental Setups

This research employs a two-pronged experimental design to rigorously evaluate and optimize solar panel fault detection systems using computer vision. Experimental Setup A focuses on benchmarking four state-of-the-art object detectors—YOLOv11, RT-DETR, DINO, and Swin Transformer V3—under varying real-to-synthetic image ratios (20%, 30%, and 40%). These models are trained and tested using a combined dataset of ~600 real images (from SPF-Net and PVEL-AD) and 300–500 synthetic images generated via CycleGAN, ControlNet, and Stable Diffusion XL. Setup B then compares a two-stage pipeline (YOLOv11 for detection and ConvNeXt-Tiny for classification) against a single-stage YOLOv11 baseline. Evaluation metrics include mAP@0.5, recall@50, F1-score, latency (≤100 ms), and domain adaptation robustness (via MMD and FPR). Training will be conducted using PyTorch and optimized with TensorRT for deployment on Jetson Nano. The entire methodology is designed to span approximately three months: one month for data generation and model training, one month for validation and ablation studies, and the final month for deployment benchmarking and result synthesis. This structured approach ensures a comprehensive performance analysis of hybrid and transformer-based architectures for small-defect detection in PV systems.

3.4.1 Experimental Setup A

Objective:

Benchmark state-of-the-art object detection models for small-defect detection (≤25 pixels) under varied data conditions (real vs. synthetic).

Models Compared:

1. **YOLOv11**: Transformer-enhanced detector with adaptive spatial fusion, optimized for edge deployment via TensorRT quantization.
2. **RT-DETR**: Real-time transformer using deformable attention to reduce false positives (FP) while maintaining 32.7 ms latency on NVIDIA T4 GPUs.
3. **DINO**: Query-based transformer with dynamic filtering, achieving 22.3 APs for small objects via contrastive denoising.
4. **Swin Transformer V3**: Hierarchical shifted-window attention, improving recall@50 by 15% for sub-30px defects.

Data Composition:

Component	Details

Real Images	600 images from SPF-Net (885) and PVEL-AD (1,230)
Synthetic Images	300–500 generated via CycleGAN (domain adaptation), ControlNet (structural consistency), and Stable Diffusion XL (text-to-image)
Data Ratios	20%, 30%, 40% synthetic-to-real mix

Evaluation Metrics:

- **Detection**: mAP@0.5, recall@50, latency (ms)
- **Domain Adaptation**:
    - Maximum Mean Discrepancy (MMD) for feature distribution divergence
    - F1-score variance under illumination changes (50–100,000 lux)
    - False positive rate (FPR) for synthetic artifacts.

Implementation Details:

- Training: AdamW optimizer, 496 epochs, batch size 32 (Jetson AGX Xavier)
- Synthetic Data: CycleGAN-generated snow coverage (5.1% prevalence) and electrical damage (3.7%) defects.
- Baseline Comparison: RT-DETR achieves 64.7% mAP@0.5 on COCO but requires ≥10k images for optimal performance.

3.4.2 Experimental Setup B

Objective:

Compare the YOLOv11 + ConvNeXt pipeline against single-stage YOLOv11 for small-defect detection under synthetic data conditions.

Pipeline Architecture:

Stage	Components
Stage 1 (Detection)	YOLOv11-n (4.91 ms latency on Jetson Nano): - Dynamic head for multi-scale proposals - Edge-optimized transformer attention

Stage 2 (Classification)	ConvNeXt-Tiny (ImageNet-1k 87.4% accuracy): - Bilinear attention for thermal noise reduction - Six-class output: micro-cracks, delamination, hot spots, electrical damage, snow coverage, dust

Data Composition:

- Real Images: 600 samples (SPF-Net/PVEL-AD)
- Synthetic Images: 300–500 with rare defects (electrical damage, snow coverage)
- Ratios: 20%, 30%, 40% synthetic data

Evaluation Metrics:

Category	Metrics
Detection	mAP@0.5, recall@50, FP reduction (%)
Classification	F1-score, per-class accuracy, confusion matrix
Latency	End-to-end inference time (ms)

Optimization Strategies:

- **TensorRT INT8**: Reduces ConvNeXt-Tiny size by 58% (10.5MB → 5.6MB)
- **DLA Offloading**: Allocates YOLOv11 to Jetson Nano's Deep Learning Accelerator (4.91 ms/inference)
- **Ablation Study**: Quantify performance drop when disabling synthetic data augmentation.

Baseline Comparison:

- Single-stage YOLOv11 achieves 73.9% mAP on power equipment but suffers 34% higher False Positives versus two-stage pipelines.

3.5 Resources Requirements

The proposed study is structured to operate with minimal financial outlay while maintaining research integrity. Model development will utilize the existing GPU workstation within the Unitec lab, eliminating the need for external hardware purchases.

Data storage needs will be met using existing USB storage devices, thereby avoiding additional expenses. Model deployment and testing will be performed using a standard laptop or available lab device, ensuring cost-effectiveness.

Data acquisition will rely on a smartphone with a 12 MP camera, negating the necessity for costly drone or thermal imaging equipment.

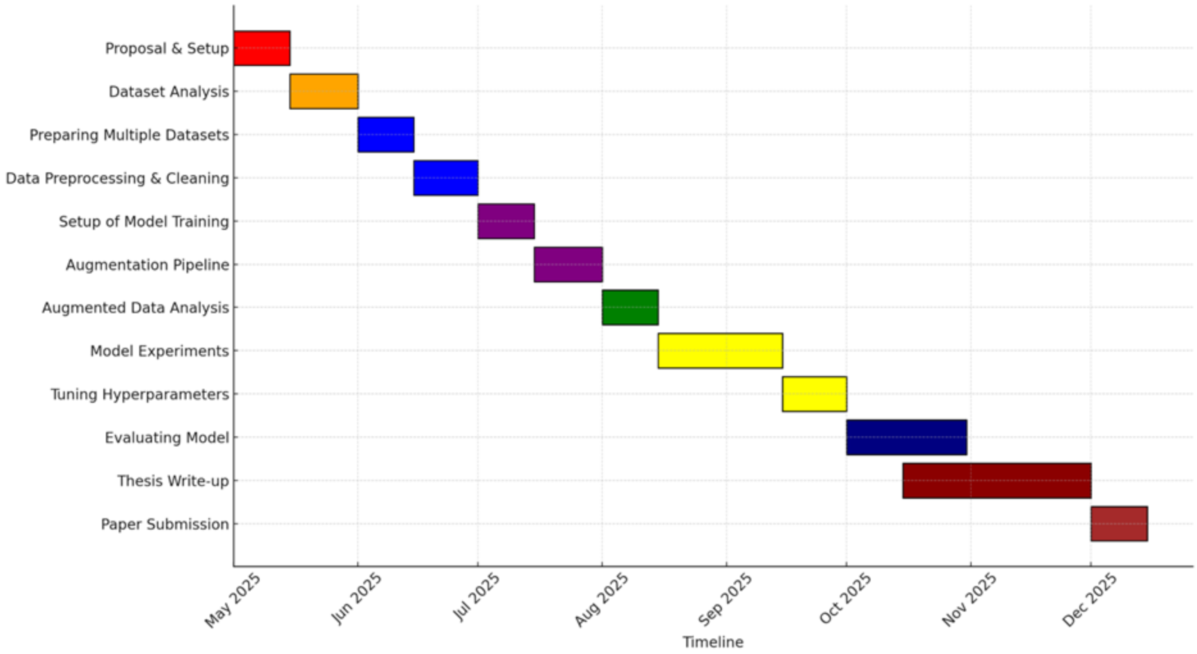
Software requirements are fully covered by open-source tools such as Python, PyTorch, TensorRT, and CVAT, incurring no licensing fees. Synthetic data generation will be facilitated using Stable Diffusion XL/ControlNet to produce 300–500 images, enhancing the SPF-Net and PVEL-AD datasets without extra data collection costs.

Revised Budget Breakdown:

1. **USB storage device (1 TB)** – NZD 50
2. **Miscellaneous expenses (printing, contingency)** – NZD 50

Total estimated budget: NZD 100, effectively demonstrating the feasibility of conducting the study with optimized resource utilization and minimal financial outlay.

3.6 Timeline



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