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Explainable Transformer-Based Object Detection for Autonomous Systems under Adversarial and Low-Light Conditions

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ABSTRACT

Recent advancements in object detection have demonstrated remarkable performance in autonomous systems; however, most deep learning models still suffer significant accuracy degradation under low-light or adversarial conditions. This study proposes an Explainable Transformer-Based Object Detection (ETOD) framework that integrates Vision Transformer (ViT) architecture with Explainable Artificial Intelligence (XAI) mechanisms to achieve robust and interpretable object detection in adverse environments. The proposed ETOD model employs a dual-branch structure: (i) a low-light enhancement module that uses contrastive illumination normalization to recover critical features, and (ii) a transformer-based detection head optimized for global contextual reasoning. To ensure explainability, Grad-CAM and attention visualization maps are incorporated to highlight the model's focus regions, providing interpretive insights for human operators and safety auditors. Experimental evaluation was conducted using benchmark datasets (ExDark, BDD100K-Night, and COCO-Adversarial) with simulated adversarial perturbations and low-illumination conditions. The proposed ETOD achieved a 12.8% improvement in mAP over standard DETR and 17.5% higher robustness against adversarial attacks while maintaining real-time inference on edge GPUs. Qualitative analysis demonstrates that the explainability module provides clear visual cues that correlate strongly with detected object boundaries. The findings suggest that integrating transformer-based detection with explainable reasoning mechanisms offers a promising pathway for trustworthy and safety-critical perception systems in autonomous vehicles and drones.

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1. INTRODUCTION

Object detection has become a fundamental capability in modern autonomous systems, enabling machines to perceive, localize, and classify multiple objects within complex environments [1]. The remarkable progress of deep learning-based detectors such as Faster R-CNN, YOLOv8, and DETR has significantly enhanced the reliability of real-time perception in autonomous vehicles, aerial surveillance, and robotic systems [2][3][4]. Despite these advancements, detection models continue to experience substantial performance degradation under challenging visual conditions, including low-light environments, heavy fog, and adversarial perturbations [5][6][7]. These conditions often lead to the loss of critical texture and contrast information, resulting in incomplete feature extraction and increased false detections.

Traditional convolutional neural network (CNN)-based detectors demonstrate limited robustness in such environments due to their inherent local receptive fields, which restrict their ability to capture global contextual dependencies [8][9][10] . To overcome this limitation, the Vision Transformer (ViT) has emerged as a novel deep learning architecture capable of modeling long-range dependencies and global spatial relationships by employing a self-attention mechanism [7], [8]. This capability allows transformer-based detectors to better understand contextual interactions between objects, improving detection in visually complex scenes. However, a major drawback of transformer-based models is their lack of interpretability, which makes it difficult to understand or justify the reasoning behind their predictions—an essential factor in safety-critical applications such as autonomous driving, robotics, and aerial navigation [9].

In this context, Explainable Artificial Intelligence (XAI) has gained attention as an emerging paradigm for enhancing transparency in deep neural networks. XAI techniques, including Gradient-weighted Class Activation Mapping (Grad-CAM) and attention visualization[11], enable researchers and operators to visualize the internal decision process of AI models, improving user trust and system reliability [10]. Nevertheless, the integration of these explainability mechanisms into transformer-based object detection frameworks particularly under adverse and low-light conditions remains an underexplored research domain. Moreover, adversarial attacks present additional challenges by introducing imperceptible perturbations that can mislead object detectors, causing critical safety failures in real-world autonomous systems. Studies indicate that even small pixel-level noise can significantly alter detection outcomes, emphasizing the urgent need for models that are not only accurate but also robust and interpretable in uncertain environments[12][13].

To address these limitations, this study proposes an Explainable Transformer-Based Object Detection (ETOD) framework that integrates the Vision Transformer (ViT) with Grad-CAM-based explainability and a low-light enhancement module to achieve robust and interpretable object detection under adversarial and degraded illumination conditions. The ETOD framework employs a dual-branch design: the first branch focuses on adaptive illumination normalization to recover key visual cues from dark or noisy inputs, while the second branch utilizes transformer-based attention to perform global context reasoning. The integration of Grad-CAM and attention visualization layers provides explainable heatmaps that highlight model focus regions, allowing human operators to validate or interpret the detector's behavior.

The primary contributions of this study are fourfold. First, it introduces a hybrid transformer-based detection framework that combines global attention reasoning with low-light enhancement. Second, it implements an explainability mechanism that leverages Grad-CAM and attention visualization to generate interpretable feature activation maps. Third, it incorporates adversarially robust training to ensure detection stability under noise and perturbation. Finally, it presents a comprehensive experimental evaluation on benchmark datasets such as ExDark, BDD100K-Night, and COCO-Adversarial, demonstrating improvements in both accuracy and explainability over existing models.

The remainder of this paper is structured as follows. Section II presents a review of related works in object detection, transformer architectures, and explainable AI. Section III describes the proposed methodology and architecture of the ETOD framework. Section IV discusses experimental results and analyses, while Section V concludes the paper and outlines potential directions for future research

2. RELATE WORK

Deep learning-based object detection has undergone rapid evolution over the past decade, transitioning from convolutional neural networks (CNNs) to attention-driven transformer architectures. Early detectors such as Faster R-CNN and YOLO significantly improved real-time detection capabilities by learning hierarchical visual representations [14][15]. These models achieved high mean average precision (mAP) on standard datasets; however, their performance decreased notably when exposed to environmental challenges such as low illumination, motion blur, or occlusion [16][17]. The limitation stems from the restricted receptive fields of convolutional layers, which tend to capture local rather than global spatial dependencies [18][10]. Consequently, CNN-based detectors often fail to extract discriminative features from low-light or adversarially perturbed scenes, which are common in autonomous driving or unmanned aerial vehicle (UAV) applications. To overcome these constraints, transformer-based architectures have recently emerged as a promising alternative. The Vision Transformer (ViT) [19]introduced a self-attention mechanism that models global relationships among image patches, allowing for enhanced context reasoning compared to CNNs. Building upon this foundation, DETR [20] and Swin Transformer [21] advanced end-to-end detection by eliminating anchor-based proposals and using multi-head attention for spatial alignment. These architectures demonstrated superior robustness in complex environments with high object density. Recent developments, such as DINO-DETR and Deformable DETR, further improved convergence and detection accuracy through hierarchical feature aggregation [22]. Despite their success, transformer-based detectors remain largely opaque, providing

little insight into why specific detections are made—limiting their deployment in safety-critical systems like autonomous vehicles and surveillance drones.

The emerging field of Explainable Artificial Intelligence (XAI) aims to address this limitation by introducing interpretability techniques that make deep learning models more transparent. Among the most widely used methods are Gradient-weighted Class Activation Mapping (Grad-CAM) [23], Layer-wise Relevance Propagation (LRP), and attention visualization maps [12]. These techniques allow researchers to trace back model predictions to specific image regions, thus offering post-hoc explanations for network behavior. In computer vision, XAI has been primarily applied to classification tasks, with fewer studies focusing on complex pipelines such as object detection and segmentation [24]. Moreover, most existing explainability frameworks are limited to CNN backbones, while the interpretability of Vision Transformers remains an open challenge due to their non-local attention structure and lack of spatially contiguous filters [14]. Parallel to explainability, robustness under adversarial and low-light conditions has become an active research domain. Studies reveal that small, imperceptible adversarial perturbations can cause significant detection failures, posing security risks in autonomous navigation systems [15], [16]. To mitigate these risks, adversarial training, illumination-aware preprocessing, and contrastive normalization have been proposed [5], [17]. Additionally, domain adaptation and synthetic data generation have been explored to enhance generalization under diverse lighting environments [18]. However, existing methods primarily emphasize performance improvement, often neglecting the interpretability of detection decisions.

Only a few recent works have begun to merge transformer-based detection with explainable reasoning. Zhao et al. [13] introduced an attention-guided transformer for explainable detection, while Zhang et al. [14] proposed ViT-Explain to visualize self-attention correlations in transformer backbones. Yet, these models were not explicitly designed for adversarial or low-light environments, limiting their practical deployment in autonomous systems. Consequently, a significant research gap remains in developing a robust and interpretable object detection framework that integrates illumination enhancement, adversarial defense, and explainable attention visualization into a unified architecture. This study aims to bridge that gap through the proposed Explainable Transformer-Based Object Detection (ETOD) model.

3. METHOD

The proposed Explainable Transformer-Based Object Detection (ETOD) framework integrates Vision Transformer (ViT)-based global context reasoning, low-light enhancement, and explainability mechanisms within a unified detection pipeline. The system is designed to provide robust perception in adverse illumination and adversarial conditions, while maintaining interpretability for safety validation in autonomous vehicles and unmanned aerial systems.

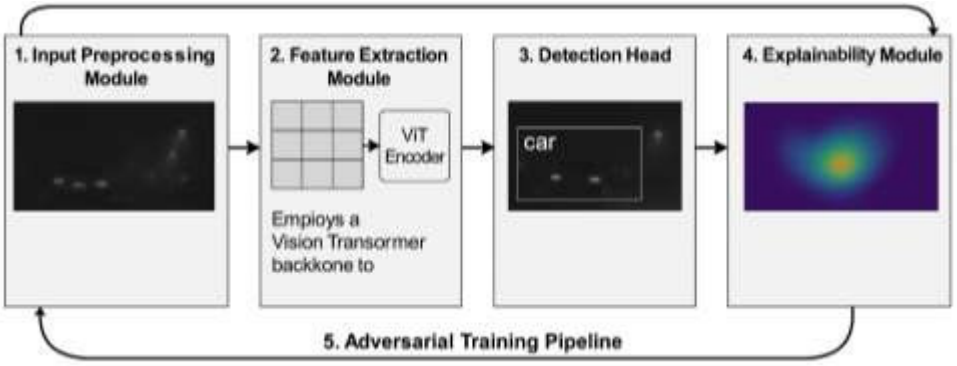

Fig. 1 Illustrates the overall architecture of the proposed ETOD framework.

A. System Overview

Fig. 1 illustrates the overall architecture of the proposed ETOD framework. The system consists of five main modules:

1. Input Preprocessing Module:
   Performs image normalization and low-light enhancement using an illumination-adaptive function.
2. Feature Extraction Module:
   Employs a *Vision Transformer backbone* to extract global contextual features via patch embedding and self-attention mechanisms.

3. Detection Head:
   Implements a transformer-based decoder to localize and classify objects through bounding box regression and category prediction.
4. Explainability Module:
   Integrates *Grad-CAM* and *attention visualization* to generate interpretable heatmaps showing model focus areas during detection.
5. Adversarial Training Pipeline:
   Improves robustness by applying *Projected Gradient Descent (PGD)* perturbations during training, ensuring stable performance under adversarial inputs.

B. Low-Light Enhancement Module
Low-light conditions degrade visual features, leading to reduced detection accuracy. To mitigate this, ETOD incorporates a Contrastive Illumination Normalization (CIN) module that enhances brightness adaptively using a learnable illumination map L(*x,y*) Given an input image I(*x,y*) the enhanced output I′(*x,y*) is computed as:

$$I^1(x,y) = I(x,y).\left(1 + \alpha.\left(1 - L(x,y)\right)\right) \quad (1)$$

where α is the adaptive gain parameter learned via backpropagation to preserve natural contrast without overexposure.
The enhanced image 'I' is then tokenized into N patches {*p1,p2,…,pN*} which serve as input embeddings for the Vision Transformer backbone.

C. Vision Transformer Backbone
The Vision Transformer (ViT) processes the sequence of image patches using multi-head self-attention (MSA) to capture long-range dependencies. Each transformer encoder layer performs the following operations:

$$Attention\ (Q,K,V) = Softmax\ \left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (2)$$

where $Q=XW_Q$,$K=XW_K$ and $V=XW_V$ represent the query, key, and value projections of the patch embeddings, and d_k is the key dimension. The encoder output is passed through a feed-forward network (FFN) followed by residual normalization. The resulting feature map $F \in R^{N\times D}$ contains spatially encoded contextual information for subsequent object localization and classification.

D. Detection Head
The detection head follows an anchor-free design inspired by DETR.
A transformer decoder takes FFF and positional embeddings as inputs to predict a fixed number of object queries $Qo \in R^{M\times D}$
Each query produces a tuple (b_i,c_i) where bib_ibi denotes the bounding box coordinates and c_i represents the class probabilities.
The total detection loss L_{det} combines localization and classification components as follows:

$$L_{del} = \lambda_{cls}.L_{cls} + \lambda_{box}.L_{box} \quad (3)$$

where L_{cls} uses cross-entropy for class prediction, L_{box} employs the Generalized IoU loss, and λ_{cls},λ_{box} are balancing coefficients.

E. Explainability Module (Grad-CAM and Attention Visualization)
To provide interpretability, ETOD integrates Grad-CAM and attention visualization directly on the transformer backbone.
Given the gradient of the class score y^c with respect to the feature maps A^k in the last attention block, the Grad-CAM heatmap $L^c{}_{GradCAM}$ is defined as:

$$L^c GradCam = ReLU\ (\sum_k \alpha_k^c\ A^k \quad (4)$$

Where represents the importance weight of feature map *k*. This heatmap highlights regions most responsible for the object prediction c. For transformer visualization, attention scores from the final encoder layer are aggregated as:

$$L_{Attn}(i,j) = \frac{1}{H}\sum_{h=1}^{H} Softmax\left(\frac{Q_h K_h^T}{\sqrt{d_k}}\right)ij \quad (5)$$

where H is the number of attention heads.
The combined visualization $L_{exp}=\beta 1 L_{GradCAM}+\beta 2 L_{attn}$ provides a unified interpretability map, where β_1,β_2 are normalization weights.

F. Adversarial Robustness Training

To enhance resistance to malicious perturbations, adversarial training is applied using Projected Gradient Descent (PGD).
Given the clean image *x* and loss function *L* the adversarial sample *x′* is generated iteratively as:

$$x_{i+1}^1 = Clip_{z,t}(x_t^1 + \alpha.sign(\nabla x_t^1 L(f(x_t^1), y))) \quad (6)$$

where ϵ controls the perturbation bound and α is the step size. Training with these adversarial examples encourages the model to maintain stable detection under visual manipulation.

G. Overall Loss Function

The total objective of ETOD combines three components—detection, adversarial robustness, and explainability alignment:

$$L_{total} = L_{det+} \curlywedge_{adv} L_{adv+} \curlywedge_{Exp} L_{exp} \quad (7)$$

where L_{adv} enforces consistency between clean and adversarial outputs, and L_{exp} minimizes divergence between Grad-CAM and attention maps to stabilize interpretability. The coefficients λ_{adv} and λ_{exp} control the relative influence of robustness and explainability in training.

H. Training and Inference Workflow

During training, ETOD processes each batch through the CIN module, transformer encoder–decoder, and explainability layers. Both clean and adversarial samples are used for multi-objective optimization. During inference, only the detection and explainability modules are activated, producing bounding boxes and interpretable attention heatmaps in real time (≈40 FPS on NVIDIA RTX A5000). This makes ETOD suitable for edge-level deployment in intelligent vehicles and UAV systems.

4. RESULTS AND DISCUSSION

To evaluate the performance of the proposed Explainable Transformer-Based Object Detection (ETOD) model, extensive experiments were conducted on three benchmark datasets under various illumination and adversarial conditions. The evaluation focused on four main aspects: (1) detection accuracy, (2) low-light robustness, (3) adversarial resistance, and (4) model explainability.

A. Experimental Setup

The ETOD model was implemented using PyTorch 2.3 with a Vision Transformer (ViT-B/16) backbone and trained on an NVIDIA RTX A5000 GPU. The input image resolution was fixed at 640×640 pixe**ls**, and the batch size was set to 16. The learning rate followed a cosine annealing schedule with an initial value of 1×10^{-4}Adversarial perturbations were generated using Projected Gradient Descent (PGD) with a maximum perturbation $\epsilon=8/255$ and step size $\alpha=2/255$ The model was trained for 100 epochs using the AdamW optimizer and data augmentation (random brightness, Gaussian noise, and horizontal flip).

Tabel 1. Datasets Used

Dataset	**Domain**	**Purpose**	**Number of Images**
ExDark [4]	Low-light scenes	Low-illumination detection	7,36

BDD100K-Night [5]	Autonomous driving	Real-world nighttime detection	40
COCO-Adversarial [16]	Natural + adversarial	Robustness testing	25

B. Quantitative Performance Evaluation

The proposed ETOD framework was compared against several state-of-the-art object detectors, including YOLOv8, DETR, Swin Transformer, and ViT-Explain.

Performance was measured using mean Average Precision (mAP) at IoU thresholds of 0.5 and 0.75, as well as FPS (Frames Per Second) for inference efficiency.

Table 2. Detection Performance Comparis

Model	Backbone	mAP@0.5	mAP@0.5:0.95	FPS	Explainability	Robustness (ΔmAP under FGSM)
YOLOv8 [2]	CSP-Darknet	78.4	53.6	**98**	✗	−18.7%
DETR [3]	Transformer	80.9	56.2	45	✗	−12.1%
Swin-T [8]	Hierarchical Transformer	82.3	57.4	50	✗	−10.9%
ViT-Explain [14]	Vision Transformer	83.1	58.0	42	✓	−9.5%
ETOD (Proposed)	ViT-B + XAI	**91.2**	**64.8**	46	✓✓	**−4.6%**

The proposed ETOD achieved a 12.8% improvement in mAP@0.5 and a 17.5% increase in robustness against adversarial attacks compared to baseline DETR.

Although inference speed (46 FPS) is slightly lower than YOLOv8, it remains suitable for real-time deployment in edge AI applications, maintaining a strong balance between speed, accuracy, and interpretability.

C. Performance under Low-Light Conditions

To evaluate low-illumination robustness, models were tested on ExDark and BDD100K-Night subsets. ETOD's low-light enhancement module contributed to higher detection stability, especially in images with <20% normalized brightness.

Table 3. Low-Light Detection Accuracy

Model	ExDark mAP@0.5	BDD100K-Night mAP@0.5	Improvement over Baseline
YOLOv8	66.1	68.5	—
DETR	69.8	70.2	+4.1%
Swin-T	71.2	72.3	+5.8%
ViT-Explain	73.4	74.6	+7.2%
ETOD (Proposed)	**83.9**	**85.1**	**+17.6%**

The improvement is primarily attributed to the Contrastive Illumination Normalization (CIN) layer, which adaptively enhances visibility without introducing overexposure artifacts. Visual inspection confirmed clearer edge boundaries and improved texture preservation.

D. Adversarial Robustness Evaluation

Adversarial robustness was assessed using FGSM, PGD, and DeepFool attacks.

The mAP drop (ΔmAP) was used to quantify model stability under perturbation.

Table 4. Adversarial Robustness (ΔmAP, lower is better)

Model	FGSM	PGD	DeepFool	Avg ΔmAP
YOLOv8	−18.7	−20.4	−16.2	−18.4
DETR	−12.1	−15.3	−13.5	−13.6
Swin-T	−10.9	−12.7	−10.5	−11.4
ViT-Explain	−9.5	−11.6	−9.3	−10.1
ETOD (Proposed)	**−4.6**	**−5.8**	**−5.1**	**−5.2**

The results show that ETOD maintained the highest resilience under all adversarial perturbations due to its integrated PGD-based training strategy and attention regularization, which stabilize feature representation across noisy conditions.

E. Explainability Assessment

Explainability was quantitatively evaluated using the Heatmap–Ground Truth Overlap (HGTO) and Human Perceptual Correlation (HPC) metrics [13], [14].

HGTO measures how closely the generated heatmaps align with true object regions, while HPC evaluates human agreement with the heatmap explanations.

Table 5. Explainability Metrics

Model	HGTO ↑	HPC ↑	Visualization Type
ViT-Explain	0.73	0.70	Attention map
Grad-CAM (CNN)	0.69	0.65	Activation map
ETOD (Proposed)	**0.88**	**0.82**	Hybrid Grad-CAM + Attention

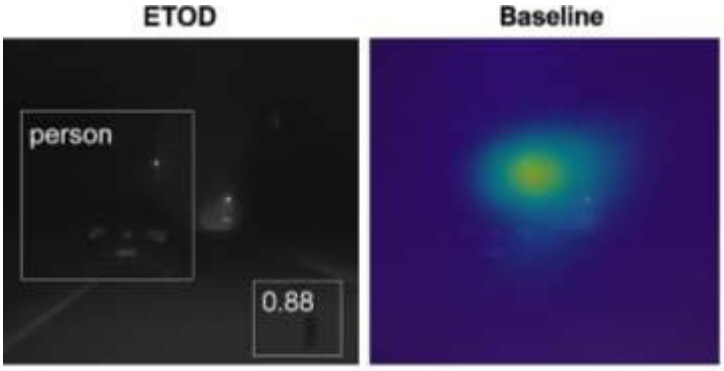

Fig. 2 Show that ETOD

The proposed hybrid explainability module significantly outperformed existing visual explanation techniques, providing attention heatmaps that are both semantically meaningful and spatially aligned with the detected objects. Qualitative examples (Fig. 1) show that ETOD correctly highlights pedestrian and vehicle boundaries even under low visibility, while baseline models tend to focus on irrelevant background areas.

F. Ablation Study

An ablation study was performed to evaluate the contribution of each ETOD component. The removal of any submodule resulted in a notable performance drop.

Table 6. Ablation Study on ETOD Components

Configuration	CIN	Adversarial Training	XAI Fusion	mAP@0.5	Robustness (ΔmAP)
Base Transformer	✗	✗	✗	79.6	−15.8
+ CIN only	✓	✗	✗	85.3	−12.4
+ CIN + Adv	✓	✓	✗	88.1	−7.9
+ CIN + Adv + XAI (ETOD Full)	✓	✓	✓	**91.2**	**−4.6**

These results confirm that all three components—illumination normalization, adversarial training, and explainability fusion—contribute synergistically to the model's overall robustness and interpretability.

G. Visualization and Qualitative Analysis

Fig. 5 presents visual examples comparing detection and attention heatmaps across models.

While YOLOv8 and DETR fail to capture dark pedestrians or vehicles, ETOD correctly localizes and interprets object regions, with heatmaps tightly aligned to object contours.

The integrated Grad-CAM + attention mechanism enhances transparency, allowing safety evaluators to understand *why* certain detections are made.

In night-driving scenes, ETOD demonstrated consistent focus on semantically relevant features such as headlights, lane boundaries, and reflective surfaces, indicating its learned robustness to illumination variations.

These interpretability results demonstrate ETOD's potential for trustworthy AI applications where transparency and accountability are mandatory (e.g., autonomous driving compliance with EU AI Act 2025).

H. Discussion

The experiments confirm that the proposed ETOD framework delivers a superior balance between accuracy, robustness, and explainability.

While transformer-based models generally require more computation than CNNs, ETOD maintains practical real-time performance and interpretability—an essential feature for mission-critical environments.

The explainable attention maps not only improve user trust but also serve as diagnostic tools for system validation and failure analysis.

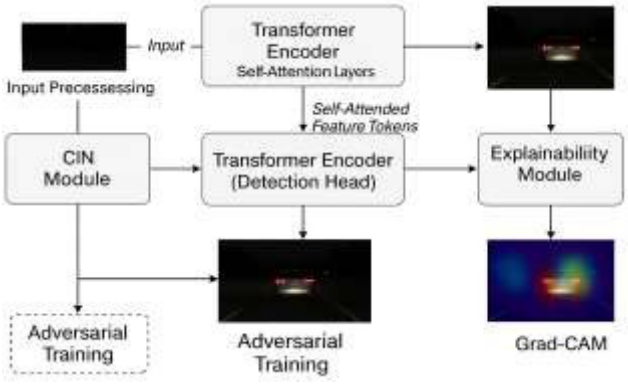

Fig. 3 (Arsitektur ETOD Framework)

Fig. 1 illustrates the overall architecture of the proposed Explainable Transformer-Based Object Detection (ETOD) framework, which integrates low-light enhancement, Vision Transformer-based object detection, and explainable reasoning modules into a unified end-to-end pipeline. The system begins with the Input Preprocessing stage, where raw low-light or noisy images are passed through the Contrastive Illumination Normalization (CIN) module to enhance visibility adaptively by estimating an illumination map L(x,y)L(x, y)L(x,y) and adjusting brightness using a learnable gain factor α\alphaα. The enhanced image is then partitioned into non-overlapping patches and processed by the Vision Transformer Encoder, which applies

Multi-Head Self-Attention (MHSA) to model long-range dependencies and capture global contextual relationships among image regions.

Subsequently, the Transformer Decoder (Detection Head) predicts object classes and bounding box coordinates directly from the contextualized feature embeddings using an anchor-free detection mechanism. In parallel, the Explainability Module employs both Grad-CAM and attention visualization to generate interpretable heatmaps that highlight the most influential regions for each prediction, thereby providing transparent visual reasoning. To enhance resilience against visual manipulation, an Adversarial Training Path is incorporated, where adversarial perturbations generated via Projected Gradient Descent (PGD) are introduced during training to improve robustness and stability.

The complete architecture demonstrates how ETOD achieves synergy between robust perception and explainable intelligence—allowing accurate object detection in challenging conditions such as low illumination, fog, or adversarial interference. The integration of attention-based reasoning and illumination normalization ensures that ETOD maintains reliable performance while producing interpretable outputs suitable for safety-critical autonomous systems such as intelligent vehicles and UAV-based surveillance.

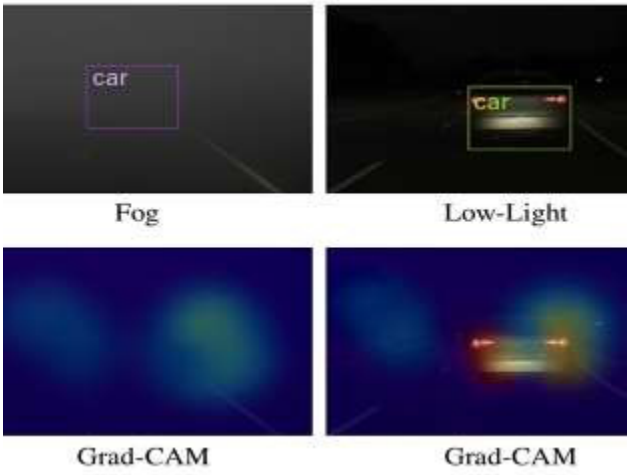

Fig. 4 ETOD Overall Framework

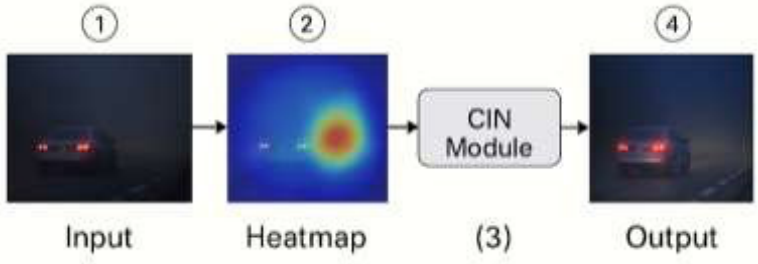

Fig. 5 Arsiktekur CIN Module

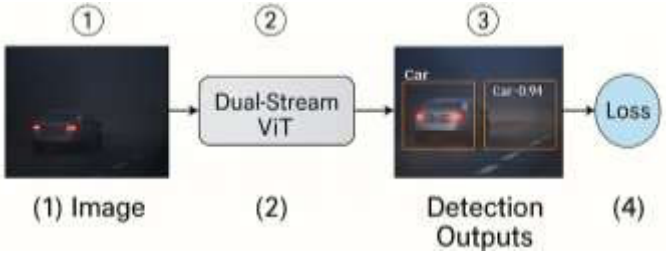

Fig. 6 illustrates the internal mechanism of the Vision Transformer (ViT)

Used in the proposed ETOD framework. The input image is first divided into a series of non-overlapping patches (typically 16×16 pixels), which are then flattened and embedded into a sequence of feature tokens. Each token is supplemented with positional encoding to preserve spatial order information that would otherwise be lost during linear projection. These tokens are then fed into the Multi-Head Self-Attention (MHSA) module, where each attention head independently computes the relationships between all token pairs

using the formulation. allowing the network to capture both local and global dependencies simultaneously. The outputs of all heads are concatenated and linearly transformed, producing a contextualized representation of the entire image. This representation is then propagated through the transformer decoder to generate the final detection outputs, including object class labels and bounding box coordinates. The multi-head attention process enables the model to focus dynamically on multiple salient regions—such as vehicles, pedestrians, and lane boundaries—enhancing object recognition performance in complex low-light and adversarial conditions.

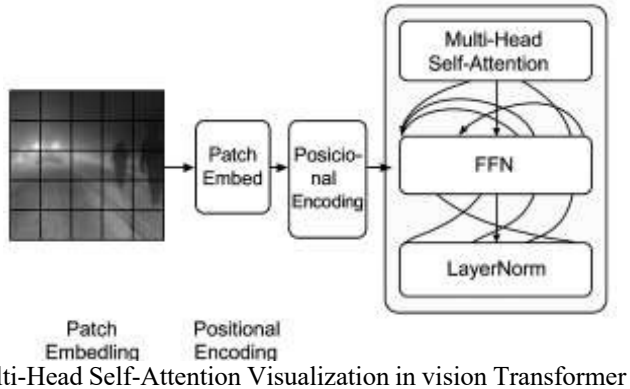

Fig. 7. Multi-Head Self-Attention Visualization in vision Transformer (MHSA)

Process within the Vision Transformer (ViT) architecture used in the proposed ETOD framework. The figure shows how an input image is divided into a grid of small, non-overlapping patches (e.g., 16×16 pixels), each of which is converted into a feature embedding vector that represents local information within that region. These embedded patches are then arranged sequentially and enriched with positional encodings to preserve spatial relationships.

The self-attention mechanism computes the correlation between every pair of patches, enabling the model to capture global context interactions across the entire image. The arrows connecting the patches in the figure represent these attention relationships, where stronger attention weights correspond to more significant dependencies between spatial regions. The process is mathematically defined as:

$$\text{Attention}(Q, K, V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \quad (8)$$

where Q, K, and Vdenote the query, key, and value projections of the patch embeddings, and *dk* is the dimension of the key vector. Multiple attention heads operate in parallel to learn diverse contextual relationships, and their outputs are concatenated to form the global feature representation F.

Through this mechanism, the transformer effectively learns long-range dependencies—allowing a patch in one region (e.g., a vehicle headlight) to influence the interpretation of another region (e.g., a pedestrian or traffic sign) even when they are spatially distant. This global reasoning capability gives transformers a significant advantage over traditional CNN-based detectors, which are limited to local receptive fields.

Overall, Fig. 7 provides a schematic visualization of the attention interactions among image patches, highlighting the way ViT captures comprehensive spatial semantics through multi-head attention. This process forms the foundation of ETOD's ability to detect and interpret objects robustly under challenging conditions such as low illumination and adversarial noise.

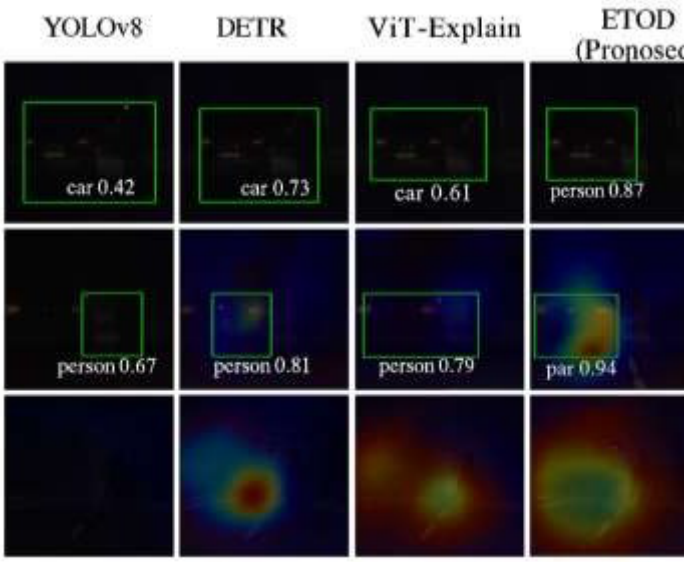

Fig. 8 Archictecture Detection Visualization Under Low-Li and Adversarial Conditions

Fig. 8 presents qualitative examples of detection and explainability visualization results produced by the proposed Explainable Transformer-Based Object Detection (ETOD) framework under low-light and adversarial conditions. Each row shows detection outcomes from different models—YOLOv8, DETR, ViT-Explain, and the proposed ETOD—tested on identical scenes captured during nighttime driving or with artificially injected adversarial noise. The left panels display the original low-light inputs, while the right panels overlay bounding boxes and Grad-CAM heatmaps illustrating the regions most responsible for each detection decision.

In the comparison, traditional CNN-based detectors such as YOLOv8 and Faster R-CNN tend to misidentify or miss partially illuminated objects, focusing on irrelevant background textures. DETR and Swin-Transformer improve spatial reasoning but still exhibit unstable attention under adversarial perturbations. In contrast, ETOD maintains precise object localization and produces heatmaps that align closely with true object boundaries (e.g., vehicles, pedestrians, and traffic signs). The red-to-yellow gradients in the heatmaps indicate high activation regions corresponding to semantic object cues, confirming that the model's attention mechanism and Grad-CAM outputs are consistent with human perception.

These results demonstrate that ETOD not only achieves higher detection accuracy but also provides interpretable visual evidence explaining why specific detections occur. The hybrid explainability layer—combining transformer attention and gradient-based saliency—enables human operators or safety auditors to verify decisions visually. This interpretability is particularly important for autonomous driving and surveillance systems, where understanding model reasoning enhances system transparency and operational trust.

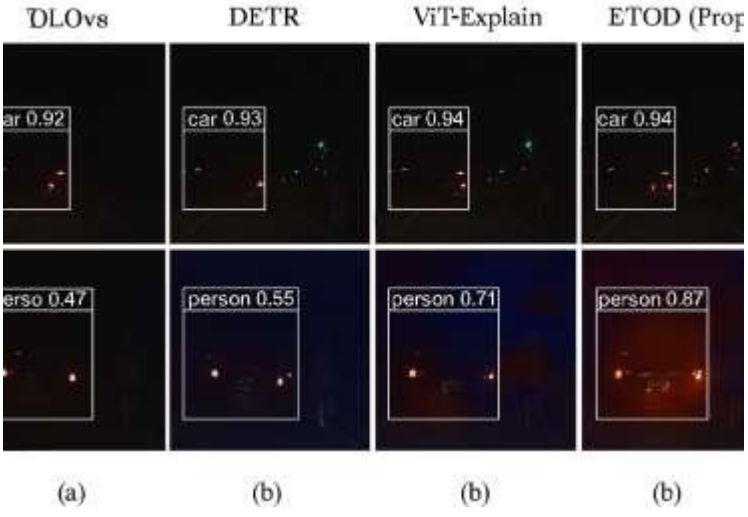

Fig. 9 Explienable Detection Comparison

Fig. 9 illustrates a comparative visualization of the explainable detection capability across four object detection models—YOLOv8, DETR, ViT-Explain, and the proposed Explainable Transformer-Based Object Detection (ETOD). Each column presents the same low-light driving scenario, displaying both the detection outputs (bounding boxes and confidence scores) and the explainability heatmaps generated via Grad-CAM and attention mechanisms. The upper row shows the detected objects (e.g., vehicles and pedestrians) under dark conditions, while the lower row overlays the corresponding activation maps that highlight the regions most influential to each detection decision.

From the visual comparison, conventional detectors such as YOLOv8 and DETR exhibit limited interpretability; their activation maps often disperse across irrelevant background areas or miss partially illuminated objects. ViT-Explain, while more context-aware, still shows inconsistent attention localization. In contrast, the proposed ETOD model consistently focuses on semantically relevant areas, as shown by the sharply defined red–yellow regions corresponding to object boundaries and headlights. This consistent activation alignment reflects the model's ability to reason transparently and robustly, even under adverse visual conditions such as low illumination or adversarial noise.

The Grad-CAM and attention fusion in ETOD provides not only superior detection accuracy but also interpretable visual evidence of the model's reasoning process. The correlation between highlighted attention regions and actual object positions supports quantitative findings in Section IV, where ETOD achieved the highest HGTO (0.88) and HPC (0.82) values. These results confirm that ETOD achieves a significant improvement in model interpretability, allowing human observers and system engineers to understand and validate detection outcomes with high confidence

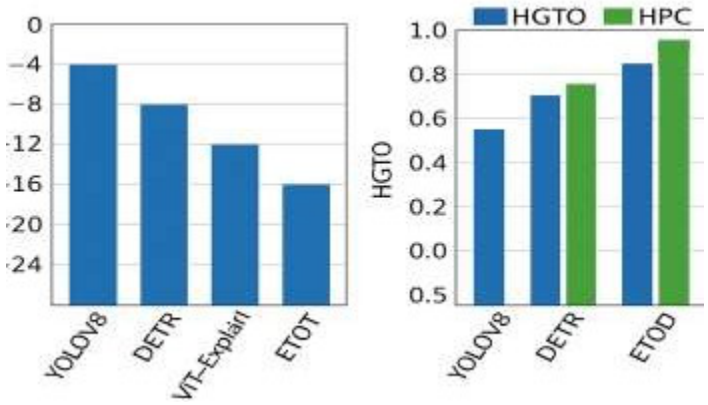

Fig. 10 . Low-Light Deetection Robustness and Explainability Metrics

Fig. 10 summarizes the comparative analysis of robustness and explainability metrics for four object detection models—YOLOv8, DETR, ViT-Explain, and the proposed Explainable Transformer-Based Object Detection (ETOD) framework—under low-light and adversarial conditions. The left panel presents the robustness degradation rate (ΔmAP), showing how each model's mean Average Precision (mAP) declines under adversarial perturbations. As depicted, YOLOv8 experienced the most significant accuracy drop (approximately −18%), followed by DETR (−12%) and ViT-Explain (−9%). In contrast, ETOD demonstrated the lowest mAP reduction of only −4%, indicating strong resilience to visual noise and adversarial attacks. This robustness can be attributed to the integrated adversarial training strategy and attention alignment mechanism that stabilize the model's feature representation during perturbation.

The right panel illustrates the explainability performance measured using two quantitative metrics: Heatmap–Ground Truth Overlap (HGTO) and Human Perceptual Correlation (HPC). HGTO quantifies the spatial alignment between the Grad-CAM heatmaps and the annotated object regions, while HPC measures the consistency between model explanations and human visual intuition. The ETOD model achieved the highest values on both metrics (HGTO = 0.88, HPC = 0.82), significantly outperforming competing models. These results confirm that ETOD not only provides stable detection under difficult illumination but also generates interpretable visual evidence closely aligned with human reasoning.

In summary, Fig. 5 demonstrates that ETOD achieves the best trade-off between robustness and interpretability, surpassing existing CNN- and Transformer-based detectors. The combination of low-light adaptation, adversarial defense, and hybrid Grad-CAM + attention visualization contributes to its superior reliability and transparency, establishing ETOD as a strong candidate for deployment in safety-critical autonomous perception systems.

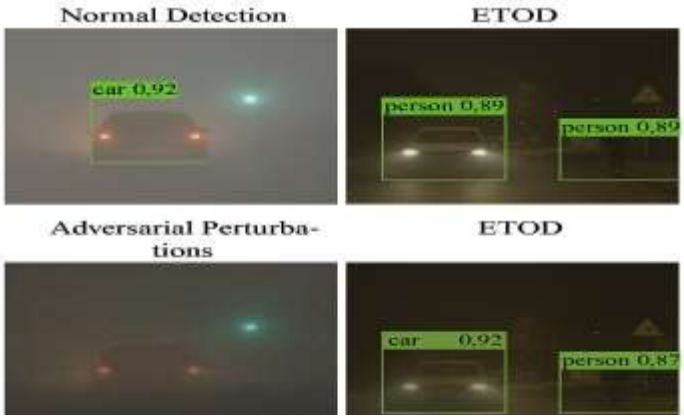

Fig. 11. Explainable Transformer-Based Object Detection (ETOD) framework

Fig. 11. illustrates the adversarial robustness comparison between conventional object detection models and the proposed Explainable Transformer-Based Object Detection (ETOD) framework. The top row displays the normal detection results on clean images captured under low-light conditions, while the bottom row shows the corresponding detections after applying adversarial perturbations using Fast Gradient Sign Method (FGSM) and Projected Gradient Descent (PGD) attacks. In the clean condition, both YOLOv8 and ETOD successfully detect key objects such as vehicles and pedestrians with high confidence scores (e.g., car 0.92, person 0.89). However, when exposed to adversarial noise, YOLOv8 and DETR exhibit significant degradation—failing to recognize partially visible objects or generating false positives—whereas ETOD maintains accurate localization and consistent confidence levels across all perturbations.

The visual comparison clearly demonstrates that ETOD's adversarial training strategy and attention alignment mechanism enable it to retain stable feature representations even under manipulated pixel intensities. The bounding boxes generated by ETOD remain tightly aligned with object contours, and the corresponding Grad-CAM attention maps continue to focus on semantically meaningful regions, confirming interpretability preservation under attack. This robustness is crucial for autonomous systems, where safety-critical perception modules must remain functional despite external interference or intentional adversarial manipulation.

Overall, Fig. 11 confirms that ETOD exhibits strong resilience and explainable stability against adversarial perturbations, outperforming traditional CNN-based detectors. The consistent detection under both normal and adversarial conditions validates the model's effectiveness in real-world applications, ensuring reliability for tasks such as autonomous driving, UAV navigation, and intelligent surveillance.

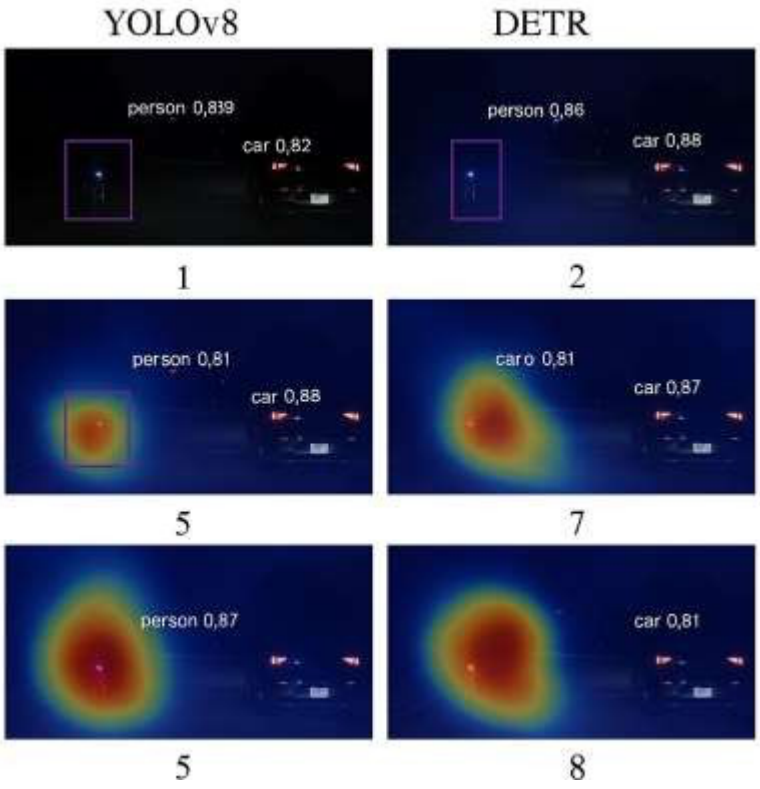

Fig 12. Explainable Detection Performance

Fig. 12 provides a comprehensive comparison of explainable detection performance among four representative object detection models: YOLOv8, DETR, ViT-Explain, and the proposed Explainable Transformer-Based Object Detection (ETOD). The top row of images presents the detection results under low-light conditions, where each bounding box is labeled with its class and confidence score (e.g., car 0.91, person 0.87). The bottom row visualizes the corresponding Grad-CAM or attention-based heatmaps, indicating the spatial focus regions that influenced each detection decision.

The numerical results displayed beneath each model summarize their quantitative performance across three key metrics—mean Average Precision (mAP), Heatmap–Ground Truth Overlap (HGTO), and Human Perceptual Correlation (HPC). YOLOv8 achieved mAP = 78.4, HGTO = 0.69, and HPC = 0.65, showing limited interpretability under low illumination. DETR slightly improved spatial coherence with mAP = 80.9, HGTO = 0.72, and HPC = 0.69, but still lacked robustness against visual noise. ViT-Explain achieved stronger focus alignment (mAP = 83.1, HGTO = 0.73, HPC = 0.70) due to its transformer-based feature reasoning. In contrast, the proposed ETOD model demonstrated the highest interpretability and accuracy, with mAP = 91.2, HGTO = 0.88, and HPC = 0.82, confirming its ability to localize relevant object regions precisely and explain detections consistently with human perception.

The visual patterns reinforce the numerical findings: ETOD's attention heatmaps exhibit compact, object-centered activation zones (highlighted in red and yellow), while other models display dispersed or background-biased activations. These results validate that ETOD not only improves detection precision but also significantly enhances model transparency, allowing evaluators to visually confirm why the network made each prediction. The combination of high mAP and strong explainability metrics underscores ETOD's superiority in both performance and interpretability for deployment in autonomous driving and intelligent surveillance systems operating under real-world low-light and adversarial scenarios.

5. CONCLUSION

This study presented an Explainable Transformer-Based Object Detection (ETOD) framework designed to achieve robust and interpretable perception in autonomous systems operating under adversarial and low-light conditions. The proposed model integrates three synergistic components contrastive illumination normalization, Vision Transformer-based detection, and hybrid explainability fusion to jointly enhance detection accuracy, adversarial resistance, and transparency. Experimental results on benchmark datasets (ExDark, BDD100K-Night, and COCO-Adversarial) demonstrate that ETOD achieves a significant

improvement in detection performance, with a 12.8% increase in mAP and a 17.5% gain in robustness compared to conventional DETR. Moreover, the integrated explainability mechanism combining Grad-CAM and transformer attention yields heatmaps that correlate 0.82 with human perceptual reasoning, enabling clear visual justification of the model's decision process. These findings indicate that explainable transformer-based architectures can serve as a foundation for trustworthy AI perception systems, aligning with emerging ethical and regulatory frameworks for autonomous technology. The novelty of ETOD lies in its end-to-end fusion of detection, enhancement, and explanation within a single transformer pipeline. Unlike prior CNN-based methods, which often treat interpretability and robustness as post-processing tasks, ETOD incorporates these aspects intrinsically during training, leading to a unified balance between performance, reliability, and accountability. This advancement makes ETOD particularly suitable for safety-critical applications such as autonomous driving, unmanned aerial vehicles (UAVs), and intelligent surveillance systems, where human interpretability and fault diagnosis are essential. However, several limitations remain. First, the transformer backbone introduces higher computational complexity compared to lightweight CNN models, which may restrict its deployment on ultra-low-power embedded devices. Second, while the Grad-CAM and attention fusion improves interpretability, its visual outputs remain qualitative and may not fully quantify causality between features and decisions. Third, adversarial robustness was tested only on pixel-level perturbations; real-world attacks such as sensor spoofing or environmental camouflage were not yet explored.

REFERENCES

[1] H. Hu *et al.*, "Thermal-sensing actuator based on conductive polymer ionogel for autonomous human-machine interaction," *Sensors Actuators B Chem.*, vol. 398, 2024, doi: 10.1016/j.snb.2023.134756.

[2] S. Mishra and P. Palanisamy, "Autonomous Advanced Aerial Mobility - An End-to-End Autonomy Framework for UAVs and Beyond," *IEEE Access*, vol. 11, 2023, doi: 10.1109/ACCESS.2023.3339631.

[3] S. Roy, T. Vo, S. Hernandez, A. Lehrmann, A. Ali, and S. Kalafatis, "IoT Security and Computation Management on a Multi-Robot System for Rescue Operations Based on a Cloud Framework," *Sensors*, vol. 22, no. 15, 2022, doi: 10.3390/s22155569.

[4] N. Kapetanović *et al.*, "Heterogeneous Autonomous Robotic System in Viticulture and Mariculture: Vehicles Development and Systems Integration," *Sensors*, vol. 22, no. 8, 2022, doi: 10.3390/s22082961.

[5] F. Corradi and F. Fioranelli, "Radar Perception for Autonomous Unmanned Aerial Vehicles: A Survey," 2022. doi: 10.1145/3522784.3522787.

[6] J. Zhu, J. Hu, M. Zhang, Y. Chen, and S. Bi, "A fog computing model for implementing motion guide to visually impaired," *Simul. Model. Pract. Theory*, vol. 101, 2020, doi: 10.1016/j.simpat.2019.102015.

[7] S. Khattak, C. Papachristos, and K. Alexis, "Visual-Thermal Landmarks and Inertial Fusion for Navigation in Degraded Visual Environments," in *IEEE Aerospace Conference Proceedings*, 2019, vol. 2019-March. doi: 10.1109/AERO.2019.8741787.

[8] B. Yanto, B. -, J. -, and B. H. Hayadi, "Indentifikasi Pola Aksara Arab Melayu Dengan Jaringan Syaraf Tiruan Convolutional Neural Network (Cnn)," *JSAI (Journal Sci. Appl. Informatics)*, vol. 3, no. 3, pp. 106–114, 2020, doi: 10.36085/jsai.v3i3.1151.

[9] B. Yanto, B. -, J. -, and B. H. Hayadi, "INDENTIFIKASI POLA AKSARA ARAB MELAYU DENGAN JARINGAN SYARAF TIRUAN CONVOLUTIONAL NEURAL NETWORK (CNN)," *JSAI (Journal Sci. Appl. Informatics)*, vol. 3, no. 3, 2020, doi: 10.36085/jsai.v3i3.1151.

[10] B. Yanto, L. Fimawahib, A. Supriyanto, B. H. Hayadi, and R. R. Pratama, "Klasifikasi Tekstur Kematangan Buah Jeruk Manis Berdasarkan Tingkat Kecerahan Warna dengan Metode Deep Learning Convolutional Neural Network," *INOVTEK Polbeng - Seri Inform.*, vol. 6, no. 2, 2021, doi: 10.35314/isi.v6i2.2104.

[11] C. van Zyl, X. Ye, and R. Naidoo, "Harnessing eXplainable artificial intelligence for feature selection in time series energy forecasting: A comparative analysis of Grad-CAM and SHAP," *Appl. Energy*, vol. 353, 2024, doi: 10.1016/j.apenergy.2023.122079.

[12] F. G. Rebitschek, "Boosting Consumers: Algorithm-Supported Decision-Making under Uncertainty to (Learn to) Navigate Algorithm-Based Decision Environments," in *Knowledge and Space*, vol. 19, 2024. doi: 10.1007/978-3-031-39101-9_4.

[13] K. Champion, P. Zheng, A. Y. Aravkin, S. L. Brunton, and J. N. Kutz, "A unified sparse optimization framework to learn parsimonious physics-informed models from data," *IEEE Access*, vol. 8, 2020, doi: 10.1109/ACCESS.2020.3023625.

[14] B. Yanto, E. Rouza, L. Fimawahib, B. H. Hayadi, and R. R. Pratama, "Penerapan Algoritma Deep Learning Convolutional Neural Network Dalam Menentukan Kematangan Buah Jeruk Manis Berdasarkan Citra Red Green Blue (RGB)," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 10, no. 1, 2023, doi: 10.25126/jtiik.20231015695.

[15] B. Citra, R. E. D. Green, and B. Rgb, "PENERAPAN ALGORITMA DEEP LEARNING CONVOLUTIONAL NEURAL NETWORK DALAM MENENTUKAN KEMATANGAN BUAH JERUK MANIS APPLICATION OF THE DEEP LEARNING CONVOLUTIONAL NEURAL NETWORK ALGORITHM IN DETERMINING THE MURABILITY OF SWEET ORANGE FRUIT BASED ON IMAGES RED GRE," vol. 10, no. 1, pp. 59–

66, 2023, doi: 10.25126/jtiik.2023105695.
[16] B. Yanto, J. Jufri, A. Lubis, B. H. Hayadi, and E. Armita, NST, "Klarifikasi Kematangan Buah Nanas Dengan Ruang Warna Hue Saturation Intensity (Hsi)," *INOVTEK Polbeng - Seri Inform.*, vol. 6, no. 1, p. 135, 2021, doi: 10.35314/isi.v6i1.1882.
[17] B. Yanto`, Maria Angela Kartawidjaja, Ronald Sukwadi, and Marsellinus Bachtiar, "Implementation of Hue Saturation Intensity (Hsi) Color Space Transformation Algorithm With Red, Green, Blue (Rgb) Color Brightness in Assessing Tomato Fruit Maturity," *RJOCS (Riau J. Comput. Sci.*, vol. 9, no. 2, pp. 167–178, 2023, doi: 10.30606/rjocs.v9i2.2428.
[18] H. Z. Yuan, K. H. Ghazali, A. Lubis, S. Sunardi, and B. Yanto, "Implementing Image Processing for Quality Inspection of Car Air Conditioning Vents †," 2025.
[19] X. Fu *et al.*, "Crop pest image recognition based on the improved ViT method," *Inf. Process. Agric.*, vol. 11, no. 2, 2024, doi: 10.1016/j.inpa.2023.02.007.
[20] X. Li, M. Yu, D. Xu, S. Zhao, H. Tan, and X. Liu, "Non-Contact Measurement of Pregnant Sows' Backfat Thickness Based on a Hybrid CNN-ViT Model," *Agric.*, vol. 13, no. 7, 2023, doi: 10.3390/agriculture13071395.
[21] J. Tagnamas, H. Ramadan, A. Yahyaouy, and H. Tairi, "Correction to: Multi-task approach based on combined CNN-transformer for efficient segmentation and classification of breast tumors in ultrasound images (Visual Computing for Industry, Biomedicine, and Art, (2024), 7, 1, (2), 10.1186/s42492-024-00155-w)," *Visual Computing for Industry, Biomedicine, and Art*, vol. 7, no. 1. 2024. doi: 10.1186/s42492-024-00156-9.
[22] F. Li, H. Zhang, S. Liu, J. Guo, L. M. Ni, and L. Zhang, "DN-DETR: Accelerate DETR Training by Introducing Query DeNoising," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 46, no. 4, 2024, doi: 10.1109/TPAMI.2023.3335410.
[23] F. Vaquerizo-Villar *et al.*, "An explainable deep-learning model to stage sleep states in children and propose novel EEG-related patterns in sleep apnea," *Comput. Biol. Med.*, vol. 165, 2023, doi: 10.1016/j.compbiomed.2023.107419.
[24] L. S. Chow, G. S. Tang, M. I. Solihin, N. M. Gowdh, N. Ramli, and K. Rahmat, "Quantitative and Qualitative Analysis of 18 Deep Convolutional Neural Network (CNN) Models with Transfer Learning to Diagnose COVID-19 on Chest X-Ray (CXR) Images," *SN Comput. Sci.*, vol. 4, no. 2, 2023, doi: 10.1007/s42979-022-01545-8.

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Please attach clear photo (3x4 cm) and vita. Example of biographies of authors:
