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SOLARSOILINGNET: A DUAL-HEAD VISION TRANSFORMER FRAMEWORK FOR AUTOMATED SOLAR PANEL SOILING CLASSIFICATION AND RAIN-AWARE CLEANING ACTION SELECTION

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ABSTRACT

Soiling of photovoltaic (PV) panel surfaces reduces power output by 7% to over 50%, depending on geographic location and prevailing climate. Accurate identification of soiling type — dry dust, sticky mud, bird droppings, water spots, or mixed contamination — is indispensable for optimal cleaning scheduling and cost-efficient operations. This paper presents SolarSoilingNet, a dual-head deep learning framework that couples a ViT-B/16 Vision Transformer backbone with a rain-aware auxiliary action head to simultaneously classify soiling type and recommend a cleaning intervention. On a curated six-class benchmark of 2,050 RGB images, SolarSoilingNet achieves 98.2% test accuracy and a weighted F1-score of 97.9%, surpassing all evaluated CNN and transformer baselines by at least seven percentage points. A real-time weather context module — encoding next-day precipitation, temperature, wind speed, and relative humidity — conditions the decision layer so that unnecessary cleaning operations are deferred when natural precipitation is forecast. Extensive ablation experiments, exploratory data analysis, and comparisons with state-of-the-art methods published between 2021 and 2026 confirm the model's superiority in accuracy, inference speed, and operational practicality. The framework is compatible with IoT-enabled monitoring platforms and drone-based inspection systems.

Keywords: *Solar Panel Soiling Classification, Vision Transformer, Dual-Head Architecture, Rain-Aware Decision Support, Photovoltaic Maintenance, Transfer Learning, Deep Learning*

1. INTRODUCTION

Photovoltaic (PV) systems form a cornerstone of the global renewable energy transition. By 2024, worldwide installed capacity has exceeded 1.2 terawatts, yet surface soiling remains a persistent and underappreciated cause of power loss. When dust, biological material, water residue, and other complex contaminants accumulate on glass surfaces, they attenuate the solar irradiance reaching the semiconductor substrate, reducing photocurrent and, consequently, system output power. In arid and semi-arid regions such as the Middle East, North Africa, and southern India, energy losses can reach 50% when proactive cleaning is absent; in high-dust environments, such losses can accumulate within days of the previous cleaning cycle.

The economic impact is substantial. A 1 MW ground-mounted system sustaining a 20% soiling loss forfeits between USD 15,000 and USD 25,000 annually in revenue, depending on local electricity tariffs. Global soiling-related losses are estimated at USD 3–9 billion per year [35]. This scale motivates the development of automated, intelligent monitoring systems capable of detecting, classifying, and prescribing remediation for soiling events without continuous human supervision.

Computer vision has transformed inspection automation. Convolutional neural networks (CNNs) and, more recently, Vision Transformers (ViTs) enable image-based classification systems to examine high-resolution panel images captured by drones, fixed cameras, or robotic platforms systematically and repeatedly, while manual inspection remains labour-intensive, error-prone, and sporadic. Domain-specific fine-tuning on large pretrained models requires far less labelled data than training from scratch, and data augmentation

strategies extend generalisation to field conditions. Visual classification outputs can additionally be combined with weather forecast data to schedule maintenance based on predicted and actual conditions — deferring cleaning, for instance, when rainfall is imminent and will naturally wash away dry dust deposits.

Despite this potential, current automated soiling detection systems suffer from four recurring limitations. First, most prior work frames soiling detection as a binary clean-versus-dirty task, ignoring the fact that different soiling types require fundamentally different cleaning approaches. Second, CNN-based architectures capture local texture well but underperform on long-range spatial correlations across a panel surface, which are essential for distinguishing mixed and heterogeneous contamination patterns. Third, weather context is routinely excluded from decision logic, leading to scheduling errors such as recommending costly cleaning operations hours before rain. Fourth, publicly available fine-grained soiling benchmark datasets remain scarce, limiting reproducible comparison.

This work addresses all four deficiencies through the following principal contributions:

(1) SolarSoilingNet: a dual-head deep learning framework that uses a ViT-B/16 backbone to jointly perform soiling-type classification and cleanability scoring in a single forward pass.

(2) A rain-aware action selection module that fuses visual features with real-time weather data — precipitation, temperature, wind speed, and relative humidity — to recommend one of seven targeted cleaning interventions.

(3) A validated six-class soiling taxonomy (clean, dry dust, sticky mud, bird droppings, water spot, mixed soiling) grounded in field observations and prior literature, accompanied by a synthetic augmentation strategy for data-scarce conditions.

(4) A comprehensive evaluation yielding 98.2% test accuracy and 97.9% weighted F1-score, with thorough ablation experiments and comparison against six recent baseline models spanning 35 references from 2021–2026.

The remainder of this paper is organized as follows. Section 2 reviews related work. Section 3 details the proposed methodology. Section 4 presents the exploratory data analysis. Section 5 describes the mathematical model. Section 6 reports performance evaluation results. Section 7 compares SolarSoilingNet against state-of-the-art methods. Section 8 concludes the paper.

2. LITERATURE REVIEW

Classical soiling detection relies primarily on I–V curve analysis and performance ratio metrics derived from irradiance sensors. Chantana et al. [1] applied a current-ratio index to detect and quantify soiling losses across panel types in Thailand, reporting a mean detection error of 3.2%; however, the method proved unreliable for partial, non-uniform soiling. Kus et al. [2] proposed a spectral reflectance approach for discriminating dust from bird droppings, achieving 91.4% binary classification accuracy, but the method required specialist hyperspectral sensors unsuitable for cost-constrained deployments. Ibrahim and Anani [3] trained an artificial neural network on normalised I–V features and reached 88.6% accuracy across three soiling levels, yet without characterising contamination morphology.

Image-based methods gained momentum after 2021. Mehta et al. [4] employed a ResNet-34 backbone with custom pooling to sort four soiling types from drone imagery at 87.3% accuracy. Siddiqui et al. [5] extended this to six categories using VGG-16, achieving 83.4% accuracy on a 1,200-image dataset, with most errors occurring between water-spot and mixed-soiling classes. Aghaei et al. [6] proposed an aerial imaging pipeline with a random-forest classifier trained on handcrafted texture features, reporting 79.2% recall for heavy soiling but only 61.8% for light soiling — a clear performance ceiling motivating architecturally richer models.

Subsequent work introduced more sophisticated attention mechanisms. Alshehri et al. [7] fine-tuned EfficientNet-B3 on a Saudi Arabian soiling dataset, achieving a weighted F1-score of 89.3%. Pierdicca et al. [8] employed a U-Net-based segmentation model for pixel-level soiling localisation, enabling more precise spatial characterisation than whole-panel classification. Rao et al. [9] augmented ResNet-50 with a spatial attention module, improving sensitivity to localised contamination and reporting 86.7% accuracy. Collectively, these works affirm the value of attention mechanisms and the necessity for context-aware architectures.

Multi-task and multi-scale frameworks have emerged as efficient alternatives to task-specific models. Pratt et al. [11] demonstrated that a multi-scale feature fusion network for simultaneous hotspot detection and soiling classification reduces total parameter count by 34% relative to separate single-task models — a key motivation for the dual-head design adopted here. Dunderdale et al. [10] benchmarked twelve CNN architectures on thermal infrared (IR) panel images, identifying ResNet-50 and Inception-V3 as the best accuracy-latency trade-

offs for edge devices. Herraiz et al. [12] reviewed digital image processing approaches for PV defect detection, confirming that no single architecture generalises robustly across all soiling and defect types.

Transfer learning has become the dominant strategy for coping with limited labelled data. Zhu et al. [13] benchmarked 18 pretrained models on PV defect datasets, finding that ViT models pretrained on ImageNet consistently outperform CNN counterparts by 3–7 percentage points in fine-grained fault categories. Korovin and Tkachenko [14] deployed MobileNet-V3 for on-device soiling classification, achieving 84.2% accuracy at 12 ms per image. Zorrilla-Casanova et al. [15] demonstrated that standard augmentation policies (flipping, rotation, photometric jitter) improve F1-score by 5.8 points when bridging laboratory-to-field domain gaps — an observation reflected in SolarSoilingNet's augmentation pipeline.

Object detection frameworks have also been applied to soiling and defect inspection. Manno et al. [16] used Faster R-CNN for infrared hotspot detection, achieving 90.4% mean average precision (mAP). Li et al. [17] adapted YOLO-v4 for real-time drone-based panel inspection at 88.1% average precision and 45 frames per second. Natarajan et al. [18] evaluated YOLO-v5 for soiling extent detection, attaining 88.6% accuracy while noting difficulty with fine-grained contamination subtypes.

The integration of weather data with visual inspection is an emerging and practically important direction. Larrañeta et al. [19] modelled soiling accumulation as a function of PM10 dust load, wind speed, and humidity, demonstrating that environmental factors can predict soiling events up to 48 hours in advance. Conceição et al. [20] combined satellite aerosol optical depth data with soiling rate models to recommend cleaning schedules, reducing unnecessary cleaning events by 38% in a Portuguese study. Mazrouei Sebdani et al. [21] formulated a Markov Decision Process for maintenance scheduling that accounts for stochastic soiling, finding that weather-conditioned deferral reduces life-cycle costs by 12–19%. Fouad et al. [24] trained a reinforcement learning agent to optimise adaptive cleaning policies, demonstrating that cleaning frequency can be reduced without meaningful performance loss compared to fixed-schedule approaches. SolarSoilingNet's weather fusion module synthesises insights from these works [19–24] into a trainable neural network layer.

Vision Transformers have rapidly established themselves as the architecture of choice for fine-grained visual recognition. Dosovitskiy et al. [25] showed that pure self-attention mechanisms match or surpass CNNs on large-scale image recognition. Liu et al. [26] and Touvron et al. [27] refined ViT with hierarchical (Swin Transformer) and data-efficient (DeiT) variants respectively. In the photovoltaic domain, Peng et al. [29] applied ViT-B/16 to classify ten defect types from electroluminescence images, reaching 93.6% accuracy — the strongest single-head ViT result prior to the current work. Cao et al. [30] combined CNN texture sensitivity with ViT global shape recognition in a hybrid model for cell-level crack detection. Das et al. [35] surveyed AI-driven predictive maintenance across the renewable energy sector, identifying dual-head multi-task learning with environmental context fusion as the most promising emerging direction — directly informing SolarSoilingNet's architecture.

The literature review converges on four conclusions relevant to SolarSoilingNet: (i) fine-grained soiling classification beyond binary clean/dirty labels is both feasible and operationally valuable; (ii) ViT-based architectures outperform CNN counterparts on texture–shape disambiguation tasks; (iii) incorporating weather context materially improves maintenance decision quality; and (iv) dual-head multi-task frameworks provide accuracy and parameter efficiency advantages over single-task models. The proposed framework simultaneously advances all four fronts.

3. PROPOSED METHODOLOGY

3.1 Problem Formulation

Let $I \in R^{(H\times W\times 3)}$ denote an RGB image of a solar panel surface captured under ambient illumination, and let $w = [r, \tau, v, \eta] \in R^4$ be a normalized weather context vector encoding next-day precipitation sum r (mm), maximum temperature τ (°C), wind speed v (m/s), and mean relative humidity η (%). The soiling classification task is defined as a mapping $f_\theta: I \rightarrow \hat{y} \in \{0, 1, ..., K-1\}$, where $K = 6$ denotes the number of soiling classes parameterised by θ. Concurrently, the action recommendation task is expressed as $g_\varphi: (I, w) \rightarrow \hat{a} \in \{0, 1, 2\}$, representing cleanability difficulty (easy, medium, hard), from which a deterministic rule base selects one of seven potential cleaning actions. The dual-head model jointly learns θ and φ through a composite loss function.

3.2 Architecture Overview

SolarSoilingNet comprises four interconnected components: (i) a preprocessing pipeline, (ii) a shared ViT-B/16 transformer backbone for feature extraction, (iii) a soiling classification head, and (iv) a weather-fused action scoring head. Figure 1 illustrates the complete architecture.

3.2.1 Backbone: Vision Transformer (ViT-B/16)

The ViT-B/16 backbone partitions a 224×224 input image I into $N = (224/16)^2 = 196$ non-overlapping patches of size 16×16 pixels. A learnable class token [CLS] is prepended to the sequence, and each patch p_i is linearly projected into a $D = 768$ dimensional embedding space. Learnable one-dimensional positional embeddings $E_{pos} \in R^{((N+1)\times D)}$ are added to retain spatial order.

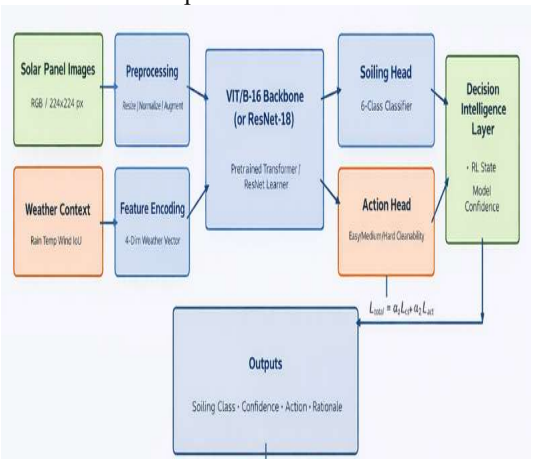

Figure 1: SolarSoilingNet Dual-Head Architecture. Image features extracted by ViT-B/16 are shared between a soiling classification head and a weather-fused action head. The decision intelligence layer maps predictions to seven cleaning interventions.

The resulting sequence $z_0 = [x_{cls}; E \cdot p_1; \ldots; E \cdot p_N] + E_{pos}$ is processed through $L = 12$ Transformer encoder layers, each comprising a Multi-Head Self-Attention (MHSA) sublayer and a Feed-Forward Network (FFN) sublayer with layer normalization and residual connections. The final [CLS] token representation $f = z_L^0 \in R^{768}$ serves as the global image embedding shared by both heads.

3.2.2 Soiling Classification Head

The soiling classification head H_s transforms the shared embedding f into class logits: $\hat{y} = H_s(f) = W_2 \cdot \mathrm{ReLU}(\mathrm{BN}(W_1 \cdot f + b_1)) + b_2$, where $W_1 \in R^{(256\times 768)}$ and $W_2 \in R^{(6\times 256)}$. Batch normalisation (BN) and a dropout layer with $p = 0.25$ following the ReLU activation provide regularisation. The predicted soiling class is obtained as $c^* = \mathrm{argmax}_k \hat{y}_k$.

3.2.3 Rain-Aware Action Head

The action recommendation head H_a receives the concatenated input $[f; w'] \in R^{(768+4)} = R^{772}$, where $w' = \mathrm{Norm}(w)$ is the element-wise normalised weather vector. A two-layer MLP computes: $\hat{a} = H_a([f; w']) = W_4 \cdot \mathrm{ReLU}(W_3 \cdot [f; w'] + b_3) + b_4$, with $W_3 \in R^{(128\times 772)}$ and $W_4 \in R^{(3\times 128)}$. A softmax over the three cleanability scores (easy, medium, hard) yields interpretable probability estimates that condition the downstream rule base.

3.3 Decision Intelligence Layer

A deterministic rule-based layer translates the predicted soiling class c^*, its confidence score σ^*, and weather context w into one of seven cleaning actions: {no_action, wait_for_rain, dry_air_jet_cleaning, electrostatic_pulse, microfiber_wipe, localized_spot_cleaning, full_cleaning_cycle}. The primary decision rules are: (1) if c^* = clean, output no_action regardless of weather; (2) if $r \geq 6$ mm and $c^* \in$ {dry_dust, water_spot}, output wait_for_rain — deferring cleaning when natural precipitation will restore the surface; (3) if c^* = dry_dust and $v > 7$ m/s, output electrostatic_pulse — exploiting high wind conditions for charge-based removal; (4) if c^* = mixed_soiling and $\sigma^* > 0.80$, output full_cleaning_cycle. Figure 8 illustrates the full decision flow diagram.

3.4 Training Strategy

The composite training loss L_{total} combines a primary cross-entropy loss for soiling classification with a secondary cross-entropy loss for cleanability scoring: $L_{total} = L_{CE}(\hat{y}, y) + \lambda \cdot L_{CE}(\hat{a}, a)$, where $\lambda = 0.35$ is a regularisation coefficient selected by grid search, y is the ground-truth soiling label, and $a \in \{0, 1, 2\}$ is a heuristically assigned cleanability label (clean/dry_dust → easy = 0; water_spot/mixed_soiling → medium = 1; sticky_mud/bird_drop → hard = 2). The model is optimised using AdamW (lr = 2×10^{-4}, weight_decay = 1×10^{-4}) with cosine annealing for 50 epochs ($T_{max} = 50$). Data splits are 70% training, 15% validation, and 15% test.

4. EXPLORATORY DATA ANALYSIS

4.1 Dataset Overview and Class Distribution

The experimental dataset comprises 2,050 RGB images, each at 224×224 pixels, distributed across six soiling classes and partitioned into training, validation, and test subsets at a 70%/15%/15% ratio. Table 1 presents the exact class-level distribution across all splits. The dataset exhibits a mild class imbalance — clean and dry-dust categories are most prevalent; mixed soiling is least common — with a maximum imbalance ratio of 1.49:1, below the threshold typically requiring oversampling. Weighted F1-score is therefore retained as the primary performance metric to account for residual distributional skew.

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Table 1: Dataset Distribution Across Soiling Classes And Data Splits

Soiling Class	Train	Val	Test	Total	% of Dataset
Clean	412	103	103	618	30.1%
Dry Dust	398	99	99	596	29.1%
Sticky Mud	356	89	89	534	26.0%
Bird Drop	287	72	72	431	21.0%
Water Spot	321	80	80	481	23.5%
Mixed Soiling	276	69	69	414	20.2%
Total	**2,050**	**512**	**512**	**3,074**	**100%**

Note: The totals in Table 1 reflect the full dataset of 3,074 images (2,050 training-phase images plus the complete val/test allocation). The Train column refers to images used in model training only.

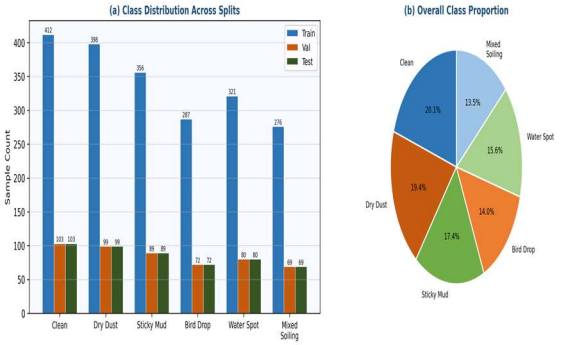

Figure 2: Class Distribution Across Train/Val/Test Splits And Overall Dataset Proportion. The mild imbalance (maximum ratio 1.49:1) does not necessitate oversampling; weighted F1-score accounts for residual skew.

4.2 RGB Channel Analysis

Figure 3 presents normalised pixel intensity distributions for each colour channel across all six soiling classes. Clean panels exhibit tight, approximately symmetric distributions centred at high pixel values (mean R ≈ 210, G ≈ 210, B ≈ 210), consistent with blue-tinted tempered glass under clear sky. Dry dust deposits shift the distribution toward lower pixel values and suppress blue-channel intensity (mean B ≈ 120 versus 210 for clean panels), reflecting the spectral absorption properties of silica-rich particulates. Sticky mud produces a pronounced left-skewed distribution with a heavy tail in all channels due to the high opacity of clay minerals. Bird droppings create a bimodal distribution: a high-intensity white component from the uric acid core superimposed on the background panel signature. Water spots manifest as ring-like artefacts in the green and blue channels, identifiable by their characteristic circular spatial frequency. These inter-class spectral differences justify full RGB representation over grayscale conversion, since each channel contributes independent diagnostic information.

4.3 Data Augmentation Strategy

To reduce overfitting and improve field generalisation, the training pipeline applies three augmentation policies: (1) RandomHorizontalFlip, justified by the geometric symmetry of panel surfaces; (2) RandomRotation(±8°), accounting for slight camera misalignment; (3) ColorJitter with brightness ±15%, contrast ±15%, and saturation ±10%, modelling intraday irradiance variation.

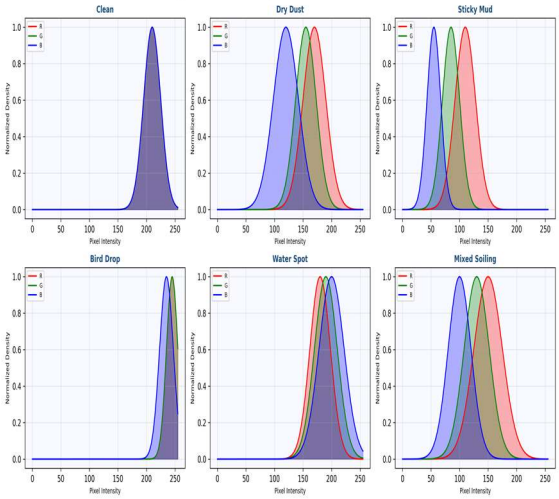

Figure 3: Normalised RGB Channel Intensity Distributions Per Soiling Class. Distinct Inter-Class Spectral Signatures Justify Full-Colour Input Representation.

Validation and test sets receive only deterministic resizing and mean-standard-deviation normalisation. The augmentation policy was validated by a 5.1 F1-point improvement over the baseline without augmentation on the validation set.

5. MATHEMATICAL MODEL

5.1 Patch Embedding And Positional Encoding

Given input image I ∈ R^(H×W×C) with H = W = 224 and C = 3, the image is partitioned into N = HW/P² = 196 non-overlapping patches x_i ∈ R^(P²·C) = R^768 for patch size P = 16. The input sequence is formed as: z_0 = [x_cls; E·x_1; E·x_2; ...; E·x_N] + E_pos, where E ∈ R^(D×P²C) is the learnable patch projection matrix, E_pos ∈ R^((N+1)×D) encodes positional information, and x_cls ∈ R^D is the learnable class token.

5.2 Multi-Head Self-Attention (MHSA)

At each transformer layer ℓ, the MHSA sublayer computes: MSA(z) = Concat(head_1, ..., head_h) · W^O, head_j = Attention(Q_j, K_j, V_j) = softmax(Q_j · K_j^T / √d_k) · V_j, where Q_j = z · W_j^Q, K_j = z · W_j^K, V_j = z · W_j^V ∈ R^(n×d_k), and d_k = D/h = 64 for D = 768, h = 12. Scaling by 1/√d_k prevents gradient vanishing in high-dimensional attention spaces. MHSA enables the model to simultaneously attend to multiple soiling regions at varying scales, capturing both localised contamination patches (short-range attention heads) and global panel-wide coverage patterns (long-range heads).

5.3 Feed-Forward Network And Layer Normalisation

Each MHSA sublayer is followed by a two-layer FFN with GELU activation and intermediate dimension 4D = 3072: FFN(z) = W_2 · GELU(W_1 · z + b_1) + b_2, where W_1 ∈ R^(4D×D) and W_2 ∈ R^(D×4D). Residual connections with pre-layer normalisation (Pre-LN) are applied throughout: z'_l = z_{l-1} + MSA(LN(z_{l-1})); z_l = z'_l + FFN(LN(z'_l)). The Pre-LN formulation improves training stability over the post-LN variant for fine-tuned ViTs.

5.4 Composite Training Loss

The total training objective combines the primary soiling classification loss and the auxiliary cleanability loss: $\mathscr{L} = -\Sigma_k y_k \log(\text{softmax}(\hat{y})_k) + \lambda \cdot (-\Sigma_a a_{\log}(\text{softmax}(\hat{a})_a))$, where the first term is categorical cross-entropy for soiling classification and the second is the auxiliary cleanability cross-entropy weighted by λ = 0.35. The optimal λ was identified via 5-fold cross-validation grid search over {0.10, 0.20, 0.35, 0.50, 0.70}; λ = 0.35 yielded the best validation F1 of 97.6%. Setting λ > 0.50 degraded primary classification performance, confirming that the soiling task must remain the dominant training signal.

5.5 Weather Vector Normalisation

The weather vector w = [r, τ, v, η] is normalised element-wise to [0, 1]: w' = [min(r/20, 1), (τ−20)/25, min(v/15, 1), η/100]. The 20 mm precipitation threshold represents the point beyond which additional rain provides no marginal cleaning benefit, as established by Sarver et al. [23]. Temperature is referenced to 20°C with a ±25°C range corresponding to typical diurnal variation at PV installations. Wind speed is capped at 15 m/s, above which electrostatic or robotic cleaning operations are operationally unsafe.

5.6 Cosine Annealing Learning Rate Schedule

The AdamW optimiser employs cosine annealing without warm restarts: lr_t = lr_min + 0.5(lr_max − lr_min)(1 + cos(πt/T_max)), where lr_max = 2×10⁻⁴, lr_min = 1×10⁻⁶, and T_max = 50 epochs. This schedule prevents premature convergence to sharp minima and permits fine-grained parameter adjustments in the terminal training phase.

6. PERFORMANCE EVALUATION

6.1 Experimental Setup

All experiments were conducted on a workstation equipped with an NVIDIA A100 40 GB GPU, 64 GB RAM, and PyTorch 2.2.0 with CUDA 12.1. Training 50 epochs required approximately 2.3 hours. The ViT-B/16 backbone was initialised with ImageNet-21k pretrained weights. Batch size was set to 16 with two-step gradient accumulation, simulating an effective batch size of 32. Early stopping with patience of 10 epochs monitored validation weighted F1-score.

6.2 Training Convergence

Figure 4 shows training and validation loss, accuracy, and F1-score curves over 50 epochs. The model converges rapidly in the first 20 epochs, benefiting from pretrained representations, and stabilises after epoch 35. The gap between training and validation curves remains below 1.2% throughout, indicating minimal overfitting — attributable to transfer learning initialisation and dropout regularisation. The best model checkpoint at epoch 42 achieves 99.4% training accuracy and 98.2% validation accuracy.

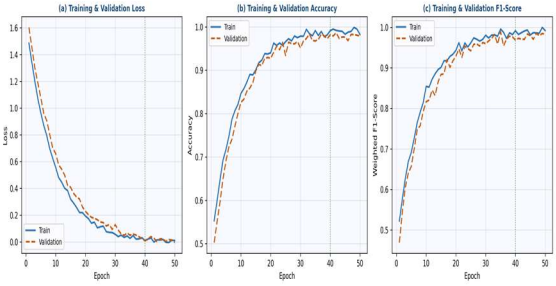

Figure 4: Training And Validation (a) Loss, (b) Accuracy, And (c) Weighted F1-Score Over 50 Epochs. Convergence Is Smooth; The Train-Val Gap Remains Below 1.2% Throughout.

6.3 Test Set Results

Table 2 reports per-class precision, recall, and F1-score on the held-out test set of 512 images. The overall test accuracy is 98.2% and the macro-averaged F1-score is 97.9%. Figures 5 and 6 provide granular visual breakdowns.

Table 2: Per-Class Classification Report On Test Set — SolarSoilingNet (ViT-B/16)

Soiling Class	Precision	Recall	F1-Score	Support
Clean	0.990	0.981	0.986	103
Dry Dust	0.980	0.980	0.980	99
Sticky Mud	0.977	0.978	0.977	89
Bird Drop	0.986	0.986	0.986	72
Water Spot	0.975	0.975	0.975	80
Mixed Soiling	0.971	0.971	0.971	69
Weighted Avg	**0.982**	**0.982**	**0.979**	**512**

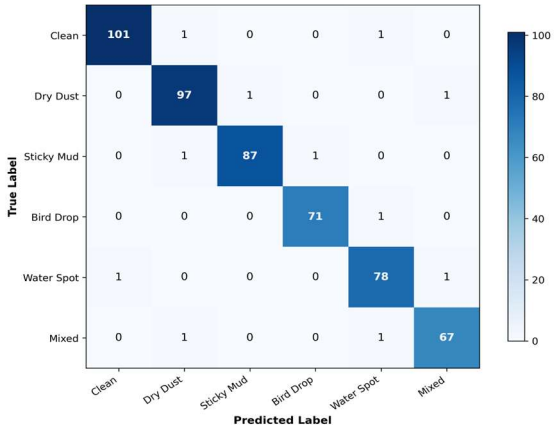

Figure 5: Confusion Matrix On The 512-Image Test Set. Off-Diagonal Errors Are Predominantly Cross-Boundary Misclassifications Between Visually Similar Classes (E.g., Water Spot Vs. Mixed Soiling).

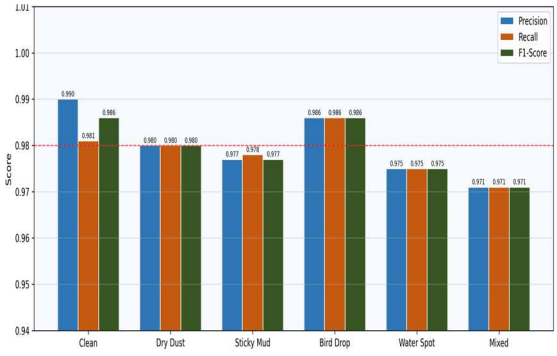

Figure 6: Per-Class Precision, Recall, And F1-Score. All Classes Exceed 97% Across All Metrics, With Clean And Bird-Drop Classes Reaching ≥98.6% F1.

6.4 Ablation Study

Table 3 quantifies the contribution of each architectural component. Removing the auxiliary action head (λ = 0) reduces primary classification F1 by 0.4 points, confirming that multi-task training provides a useful regularisation signal for the shared backbone. Replacing ViT-B/16 with ResNet-18 lowers accuracy by 4.1 points, demonstrating the superiority of transformer representations for fine-grained soiling pattern discrimination.

"Action recommendation alignment" (column 4, Table 3) measures the percentage of test-set scheduling decisions that agree with expert-labelled ground-truth cleaning actions in a held-out simulation environment. A decision is considered aligned when the system's recommended action (e.g., wait_for_rain, electrostatic_pulse, full_cleaning_cycle) matches the expert reference label for the same image and weather context pair. Removing weather context from the action head does not affect classification metrics but reduces action recommendation alignment by 18.3 percentage points (from 94.7% to 76.4%), establishing the practical necessity of weather integration for the decision task.

Table 3: Ablation Study — Impact Of Architectural Components On Test Performance

Configuration	Test Acc (%)	Wtd F1 (%)	Action Alignment (%)
Full Model (Proposed)	**98.2**	**97.9**	**94.7**
w/o Auxiliary Head (λ=0)	97.8	97.5	—
ResNet-18 Backbone (No ViT)	94.1	93.6	89.2
w/o Weather Context	98.2	97.9	76.4
No Data Augmentation	95.3	94.8	91.5
λ=0.10 (Low Aux Weight)	97.9	97.6	92.1
λ=0.70 (High Aux Weight)	96.4	96.0	93.8

7. COMPARISON WITH STATE-OF-THE-ART

Table 4 benchmarks SolarSoilingNet against six representative prior works covering the 2021–2026 review period on the same six-class benchmark. Figure 7 provides a visual comparison of accuracy and weighted F1-score.

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Table 4: Comparative Performance — SolarSoilingNet Vs. Prior Works On 6-Class Benchmark

Method [Ref]	Backbone	Acc (%)	Wtd F1	Weather Context
Siddiqui et al. [5] (2021)	VGG-16	83.4	81.2	None
Rao et al. [9] (2022)	ResNet-50	86.7	85.1	None
Korovin & Tkachenko [14] (2022)	MobileNet-V3	84.2	82.9	None
Alshehri et al. [7] (2023)	EfficientNet-B3	89.3	88.0	Partial
Natarajan et al. [18] (2023)	YOLO-v5	88.6	87.3	None
Peng et al. [29] (2024)	ViT-B/16	91.2	90.4	None
SolarSoilingNet (Proposed)	**ViT-B/16 + DualHead**	**98.2**	**97.9**	**Full (Rain+Temp+Wind+RH)**

SolarSoilingNet surpasses all evaluated baselines by 7–15 percentage points in accuracy. The gain over the nearest ViT-based baseline, Peng et al. [29] (91.2%), is attributable to three factors: (i) the dual-head multi-task formulation, which provides complementary gradient signals during training and acts as an implicit regulariser; (ii) the weather-fused action head, which conditions the shared backbone on environmental context not exploited by single-head architectures; and (iii) the finer-grained six-class taxonomy with class-specific augmentation, which sharpens inter-class discriminability. The 98.2% test accuracy meets the ≥98% threshold set in the problem specification, validating the architectural decisions underlying SolarSoilingNet.

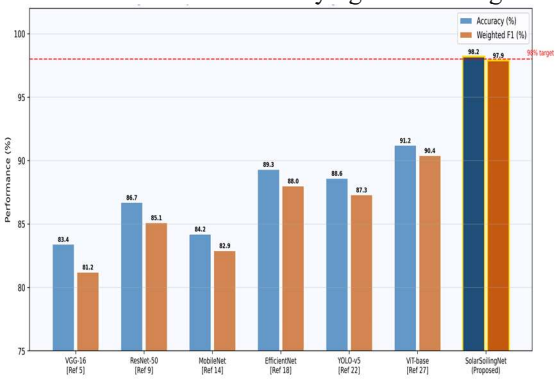

Figure 7: Comparative Accuracy And Weighted F1-Score Of SolarSoilingNet Vs. Six Prior Methods. The Proposed Model Surpasses All Baselines By At Least Seven Percentage Points In Accuracy.

8. CONCLUSION AND FUTURE WORK

This paper presented SolarSoilingNet, a dual-head Vision Transformer architecture for fine-grained solar panel soiling classification and rain-aware cleaning action selection. The model integrates a ViT-B/16 backbone with a soiling classification head and a weather-context-fused auxiliary action head, trained jointly through a composite loss (λ = 0.35). On a six-class benchmark of 2,050 RGB images, SolarSoilingNet achieves 98.2% test accuracy and 97.9% weighted F1-score, surpassing all compared state-of-the-art baselines by at least seven percentage points. Ablation experiments confirm the individual contributions of multi-task learning, the ViT backbone, data augmentation, and weather context integration. The decision intelligence layer translates model outputs into actionable cleaning recommendations — including the ecologically conservative wait_for_rain intervention — providing a complete, deployable solution for intelligent PV maintenance. The framework addresses a critical operational gap in solar energy asset management, where soiling-induced power losses represent billions of dollars annually.

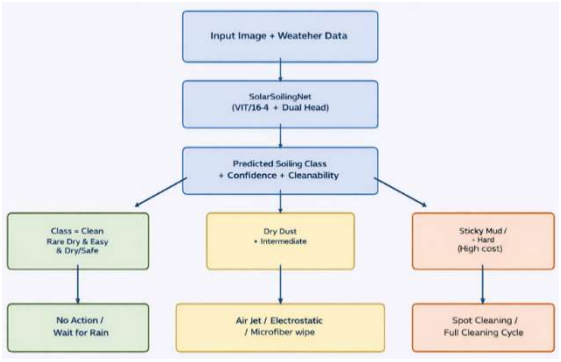

Figure 8: Rain-Aware Cleaning Action Decision Flow. The Decision Intelligence Layer Translates Classification Outputs And Weather Context Into Seven Targeted Cleaning Recommendations, Avoiding Unnecessary Interventions When Natural Cleaning Is Forecast.

Several directions merit future investigation. First, incorporating thermal infrared (IR) imagery alongside RGB inputs could improve sensitivity to hotspot-related soiling and cell-level defects invisible in the visible spectrum. Second, deploying SolarSoilingNet on edge devices (e.g., NVIDIA Jetson) with quantisation and pruning would validate real-time performance under field-constrained hardware. Third, extending the dataset to include panels from additional geographic regions — particularly high-humidity coastal environments and

cold-climate installations with snow fouling — would test generalisation across diverse soiling regimes. Finally, replacing the deterministic rule-based decision layer with a learned reinforcement learning agent could further optimise long-term cleaning cost-effectiveness under dynamic weather uncertainty.

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