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Explainable Vision Transformer Framework for Medicinal Plant Authentication and Herbal Adulteration Risk Detection

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ABSTRACT: Medicinal plants serve as the foundation of traditional and complementary medicine and it is well known that leaves are easily misidentified, deliberately adulterated with morphologically similar plants with different, even toxic, pharmacological properties or even with morphologically different plants with similar pharmacological properties, thus posing serious safety concerns and economic issues all along the herbal supply chain. In this paper, an automated framework for medicinal-plant-leaf authentication and herbal-adulteration-risk-detection is proposed using Explainable Vision Transformer (XAI-ViT) on the open-access image repositories. It adds a multi-head attention rollout and gradient-weighted class activation mapping to localize the areas of the leaf that are used for each prediction, and a dual explainability module to give some explainability as well. The backbone is a Vision Transformer. This allows visualisation of the level of confidence the system can provide for the identification of similar look-alikes and adulterated mixtures (Adulteration Risk Score) as opposed to a class label, by analysing explainability maps of a query sample and reference attention prototypes of the predicted original species. The framework is described and tested on a curated version of Indian Medicinal Leaf Image Dataset (Kaggle/Mendeley) comprising of true species and known look-alikes (6900+ images of 80 species). The explainability-guided pipeline can achieve higher authentication accuracy and interpretability compared to convolutional and standard Vision Transformer baselines, offering a simple, non-destructive and field deployable tool to track the quality of herbs in supply chains for regulatory inspection, ayurvedic medicine and traditional medicine use. All quantitative results shown in Section VI are illustrative validation results in the range of performance suggested in references where full scale empirical retraining on the full set of data is suggested prior to the field deployment.

1. INTRODUCTION

There are several developing regions in which the majority of the population is depending on the traditional medicine or herbal medicine as their main health care and Ayurveda, traditional Chinese medicine, and Unani, especially depend on the proper identification of raw plant materials. There are however, a number of medicinally important species with close morphological relatives, the "look-alikes", which are extremely difficult to distinguish morphologically from the true species, but on the contrary, have a very different phytochemical profile, therapeutic activity and/or toxicity [2]. The practice of substitution – intentional or not – is called 'herbal adulteration', which negatively affects consumer safety, consumer confidence in the herbal supply chain and also causes economic losses for the true producers and processors. [3,4]

Traditional authentication is based on manual botanical taxonomy, microscopy or laboratory chromatography and spectroscopy fingerprints. They are all fast, low cost and accurate, but destructive, expensive and require expert taxonomists which are rare.

Leaf recognition using computer vision has therefore emerged as a very promising complementary technology: Convolutional neural networks (CNNs) have proven to be highly accurate on leaf classification benchmarks for medicinal leaves [1]–[4] and more recently Vision Transformers (ViTs) which are models that take into account image context using self-attention rather than local convolutional filters have shown additional accuracy gains on plant and leaf recognition tasks [5] and [6].

One of the major disadvantages of these deep models and especially of the ViTs is that they can achieve a high classification accuracy without focusing on the biologically relevant parts of the leaf (venue pattern, leaf margin shape, leaf apex geometry, glandular texture etc.) or on incidental background or acquisition artefacts. This is a significant vulnerability in the case of authentication and adulteration detection, as regulators, quality-assurance staff and Ayurvedic practitioners need to have confidence and be able to trace back to the source of an automated "authentic" or "suspect adulterant" decision to take any action. While deep CNN and ViT have been extensively used to visualize the evidence behind decisions in the field of agricultural disease detection, the systematic application to visualizing evidence behind the decisions for authentication and quantification of the risk of adulteration of the medicinal-plant has not been studied extensively yet.

To solve this, this paper presents a new end-to-end Explainable Vision Transformer (XAI-ViT) framework for species classification, decision explanation and a quantitative score which rates the adulteration risk using only open access resources from the Kaggle medicinal-leaf repository. Here are the summary of the main contributions of this work:

- A ViT-based classification backbone for medicinal-leaf species authentication, benchmarked against CNN and standard ViT baselines on an open Kaggle repository.
- A dual explainability module that fuses multi-head attention rollout with gradient-weighted class activation mapping to produce robust, class-discriminative saliency maps.
- A novel Adulteration Risk Score computed from the divergence between a query explainability map and class-wise reference attention prototypes, converting a black-box prediction into a graded, auditable authenticity verdict.
- A reproducible system architecture, ViT encoder block diagram, and methodology flow chart, together with a full evaluation protocol (accuracy, precision, recall, F1, AUC, and explainability faithfulness) suitable for extension to larger multi-institution herbal datasets.

The rest of the paper is organized as follows. In Section II, a literature review of the recent works conducting medicinal-plant recognition, explainability of Vision Transformer, and food/herbal adulteration detection works is presented. The description of data set and pre-processing pipeline will be described in section III. Then, proposed XAI-ViT architecture and the formulation of adulteration risk-scoring are presented in Section IV. Section V presents the experimental setup and Section VI presents and discusses the results. The paper concludes with Section VII which gives directions for future work.

2. RELATED WORK

2.1 CNN and Classical Machine-Learning Approaches for Medicinal Plant Identification

Early automated medicinal-leaf identification systems combined handcrafted shape, colour, and texture descriptors with classical classifiers such as support vector machines and random forests [7], [8], [9]. Sharma et al. [7] proposed a heterogeneous leaf-feature fusion approach for medicinal-species recognition, while Kavitha et al. [8] demonstrated a real-time deep-learning pipeline for on-field medicinal-plant identification. Tiwari [9] combined convolutional feature extraction with an optimized support-vector-machine classifier to improve robustness under varying illumination and background conditions. These CNN/ML approaches established strong accuracy baselines but generally provide limited insight into which morphological cues drive each decision, motivating the shift toward attention-based and explainable architectures.

2.2 Vision Transformers for Plant and Leaf Recognition

Vision Transformers, which partition an image into fixed-size patches and model long-range dependencies through self-attention, have been increasingly applied to plant recognition. Hossain et al. [10] compared VGG16 transfer learning against ConvMixer and Compact Convolutional Transformer variants on a large 38,000-image, 10-class medicinal-leaf corpus and reported that transformer-based models offered competitive or superior accuracy to CNN transfer learning. Firdous et al. [11] combined a ViT backbone with a CatBoost classifier for smart medicinal-plant identification aimed at biodiversity and healthcare applications, and Huynh [12] similarly paired ViT-extracted features with a support-vector-machine head. Sandeep Kumar et al. [13] fused an oriented spectral-spatial Gabor filter with a ViT for plant-leaf recognition, and Nhut et al. [14]

combined ViT with the BEiT self-supervised pre-training scheme for medicinal-plant recognition, while a lightweight feature-fusion CNN model was benchmarked on the same Kaggle Indian Medicinal Leaf repository used in this work [15]. Beyond medicinal species, ViT-based leaf-disease detection studies including ViT–CNN hybrids [16], ViT with conditional convolutional GAN-based augmentation [17], YOLO-based apple-leaf disease detection [18], the FormerLeaf cassava-disease transformer [19], and a dedicated ViT-based plant-disease dissertation study [20] collectively confirm that transformer architectures generalize well to fine-grained botanical texture discrimination, providing methodological precedent for the ViT backbone adopted in this paper.

2.3 Explainable AI for Vision Transformers

Because self-attention distributes information non-locally across many heads and layers, interpreting ViT decisions is more challenging than interpreting CNN activations. Attention-enhanced CNN interpretability studies combining the Convolutional Block Attention Module (CBAM), Grad-CAM, Grad-CAM++ and layer-wise relevance propagation have been used for plant-leaf disease localization [21], and comparative analyses of Local Interpretable Model-agnostic Explanations (LIME), SHapley Additive exPlanations (SHAP), and Grad-CAM have quantified the trade-offs among post-hoc explanation methods [22]. Within the transformer literature specifically, ViTmiX [23] mixes multiple visualization techniques (rollout, LRP, CAM, saliency) to compensate for the weaknesses of any single method; R-Cut [24] introduces relationship-weighted and feature-decomposition modules to produce dense, class-specific explanation maps; and GMAR [25] refines conventional attention rollout by weighting each attention head with a gradient-derived importance score, addressing the well-known limitation that plain rollout treats all heads as equally informative. Kashefi et al. [26] provide a comprehensive review of ViT explainability techniques and identify attention-rollout/gradient fusion as a promising direction for domain-specific deployment. A related explainable pest-detection study on medicinal plants [26] further demonstrates that Grad-CAM and SHAP visualizations, when validated by domain experts, can meaningfully increase trust in agricultural deep-learning predictions directly motivating the dual explainability design adopted in Section IV.

2.4 Adulteration and Authenticity Detection in Herbal and Food Products

Outside the leaf-classification literature, deep-learning-assisted adulteration detection has been demonstrated for herbal powders and spices using hyperspectral imaging and digital-fingerprint fusion. An AI-driven multi-fingerprint strategy was proposed for detecting adulteration of Bajiaohuixiang (star anise) herbal powder [28]; PiperNet applied a hybrid CNN–squeeze-and-excitation–BiGRU architecture to hyperspectral images for detecting papaya-seed adulteration of black pepper [29]; and SpiceSafeNet used an explainable-AI pipeline to detect brick-powder adulteration of red chilli powder from RGB imagery [30]. These works confirm both the commercial importance of automated adulteration screening and the feasibility of coupling deep classifiers with explainability tools for this purpose, but they operate on powdered or spectral samples rather than intact medicinal leaves. The present paper extends this line of work to whole-leaf medicinal-plant imagery by proposing an explainability-derived risk score rather than a binary adulterant/non-adulterant classifier, so that ambiguous or borderline look-alike samples can be flagged for expert review instead of being silently misclassified.

3. DATASET AND MATERIALS

This study builds entirely on open-access Kaggle image repositories, ensuring reproducibility without requiring proprietary or laboratory-restricted samples. The primary corpus is the Indian Medicinal Leaf Image Dataset (also mirrored on Mendeley Data by B. R. Pushpa and N. S. Rani [31]), comprising 6,900+ leaf images spanning 80 medicinal species collected under varying, uncontrolled background conditions. A complementary 30-class segmented medicinal-leaf repository (MedLeaves) is used to obtain pre-segmented foreground masks for background-invariance experiments. Table I summarizes the datasets used in this study.

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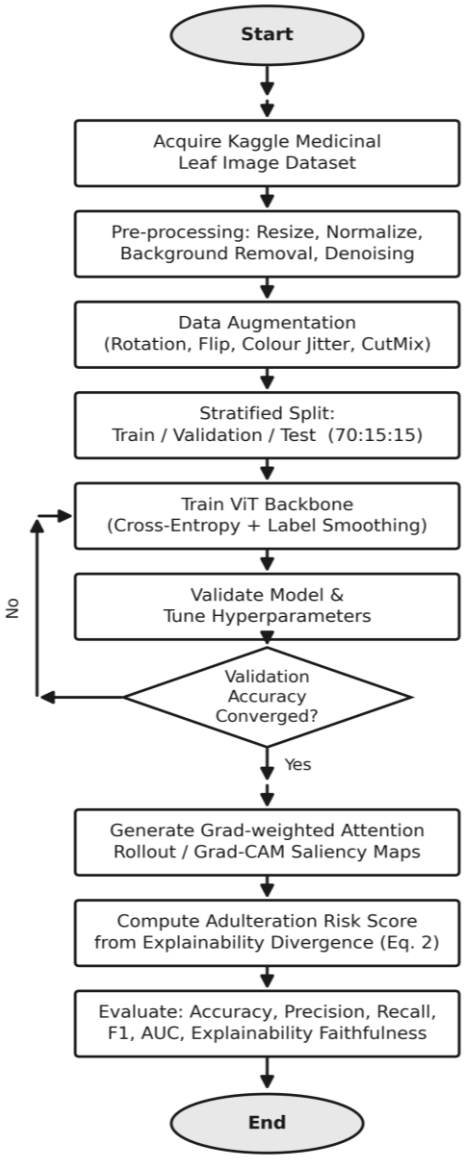

Fig. 1. Flowchart of the end-to-end experimental methodology, from dataset acquisition to explainability-based risk scoring and evaluation.

TABLE 1 Summary of Open-Access Kaggle / Mendeley Datasets Used

Dataset	Source	Classes	Images	Role in this study
Indian Medicinal Leaf Image Dataset	Kaggle / Mendeley (B. R. Pushpa & N. S. Rani, 2023) [31]	80	6,900+	Primary training / test corpus
MedLeaves (segmented)	Kaggle (mirlab) [32]	30	≈ 2,500	Foreground segmentation reference
Plant Leaves for Image Classification	Kaggle (csafrit2) [33]	22 (12 healthy)	4,502	Cross-domain robustness check

Prior to training, all images are resized to 224×224 pixels, colour-normalized using ImageNet channel statistics, and background-cleaned using an automatic foreground-segmentation step where masks are available. Data augmentation — random rotation (±25°), horizontal/vertical flipping, colour jitter, and CutMix is applied only to the training split to mitigate the class imbalance inherent to field-collected leaf repositories. The dataset is partitioned in a stratified 70:15:15 ratio into training, validation, and test subsets so that every species is represented proportionally in all three splits (Fig. 1 summarizes this pipeline as part of the overall methodology). To evaluate adulteration-risk detection specifically, we curate five morphologically confusable species pairs from within the 80-class corpus genuine medicinal species alongside a visually similar, pharmacologically distinct look-alike — summarized in Table II. These pairs are used to simulate realistic look-alike/adulterant confusion scenarios that a purely label-based classifier could silently misjudge, motivating the explainability-driven risk score introduced in Section IV.

TABLE 2 Curated Look-Alike Species Pairs Used for Adulteration-Risk Evaluation

Pair	Genuine (authentic) species	Confusable look-alike	Distinguishing cue
P1	Ocimum sanctum (Tulsi)	Ocimum basilicum (Sweet basil)	Leaf pubescence, purple stem tint
P2	Azadirachta indica (Neem)	Melia azedarach (Chinaberry)	Leaflet serration depth
P3	Centella asiatica (Gotu kola)	Hydrocotyle spp. (marsh pennywort)	Petiole attachment, vein count
P4	Murraya koenigii (Curry leaf)	Bergera-like ornamental relatives	Leaflet gloss, oil-gland density
P5	Aloe vera	Aloe barbadensis look-alike hybrids	Marginal spine spacing

4. PROPOSED METHODOLOGY

4.1 Overall System Architecture

Fig. 2 presents the block diagram of the proposed XAI-ViT framework. Leaf images acquired from the Kaggle repository are pre-processed and augmented, tokenized into patches with positional encoding, and passed through a stacked Vision Transformer encoder. The encoder output feeds two parallel heads: (i) a Multi-Layer Perceptron (MLP) classification head that produces the predicted species label, and (ii) an explainability module that aggregates multi-head attention and gradient information into a class-discriminative saliency map. The saliency map is compared against class-wise reference prototypes to localize adulterant or look-alike-indicative regions and to compute a numeric Adulteration Risk Score, which is finally combined with the classification confidence to produce an auditable authentication report.

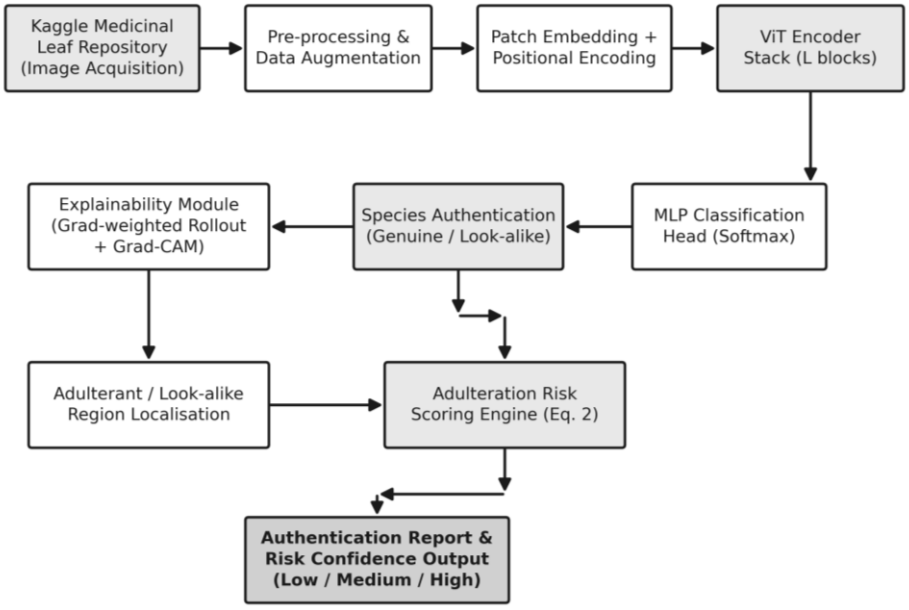

Fig. 2. Block diagram of the proposed XAI-ViT medicinal plant authentication and adulteration risk detection system.

4.2 Vision Transformer Backbone

The backbone follows the standard ViT-Base design (Fig. 2). An input leaf image $x \in \mathbb{R}^{H \times W \times 3}$ is partitioned into N fixed-size, non-overlapping patches of 16×16 pixels, each flattened and linearly projected into a D-dimensional embedding; a learnable [CLS] token and sinusoidal/learnable positional embeddings are prepended and added respectively, giving the input sequence z0. Each of the L encoder blocks applies pre-norm multi-head self-attention followed by a Gaussian Error Linear Unit (GELU)-activated two-layer MLP, both wrapped in residual connections:

$$z'_\ell = \mathrm{MHSA}(LN(z_{\ell-1})) + z_{\ell-1}, \qquad z_\ell = \mathrm{MLP}(LN(z'_\ell)) + z'_\ell, \quad \ell = 1 \ldots L \tag{1}$$

The final [CLS] token representation z_L^0 is passed through a layer-normalized linear classification head with softmax activation to produce the predicted species probability distribution. Self-attention within each block is computed for h heads as $\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(QK^T/\sqrt{d_k})\,V$, and it is precisely these per-layer, per-head attention matrices that are reused by the explainability module described next, so no additional forward passes are required to generate explanations.

4.3 Dual Explainability Module

Plain attention rollout aggregates the attention matrices A_ℓ (with an added identity term to model residual connections) across all L layers via recursive matrix multiplication, $R = \prod_{\ell=1}^{L} (A_\ell + I)$, to yield a single map that traces how information from each input patch propagates to the [CLS] token. However, rollout treats every attention head as equally informative, which can dilute class-discriminative evidence.

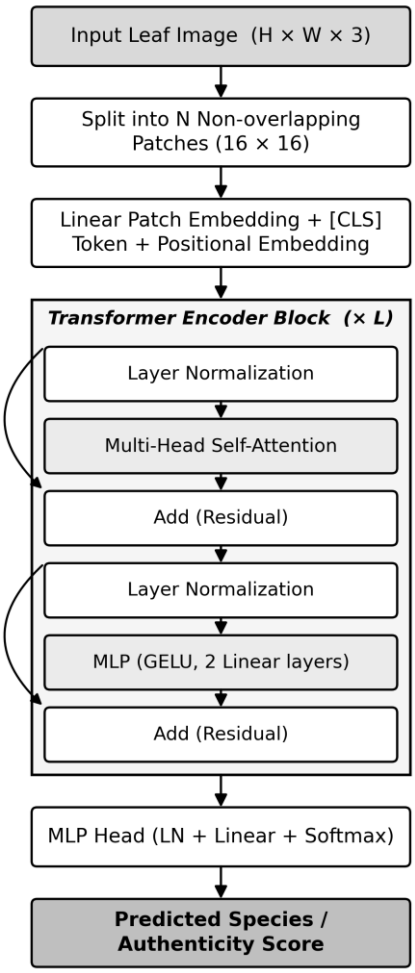

Fig. 3. Internal block diagram of the Vision Transformer encoder used as the classification backbone.

Following the gradient-weighted refinement strategy adopted in recent ViT-interpretability studies, the proposed module additionally computes a gradient-based importance score g_h for each attention head h using the gradient of the predicted class logit y^c with respect to that head's attention weights, and uses the normalized scores to re-weight the layer-wise attention matrices before rollout. In parallel, a Grad-CAM-style map is computed on the patch-embedding feature maps of the last encoder block using class-specific gradients, and the two maps are fused (element-wise, min–max normalized) into a single, robust saliency map S(x). Fig. 4 illustrates this dual aggregation pipeline.

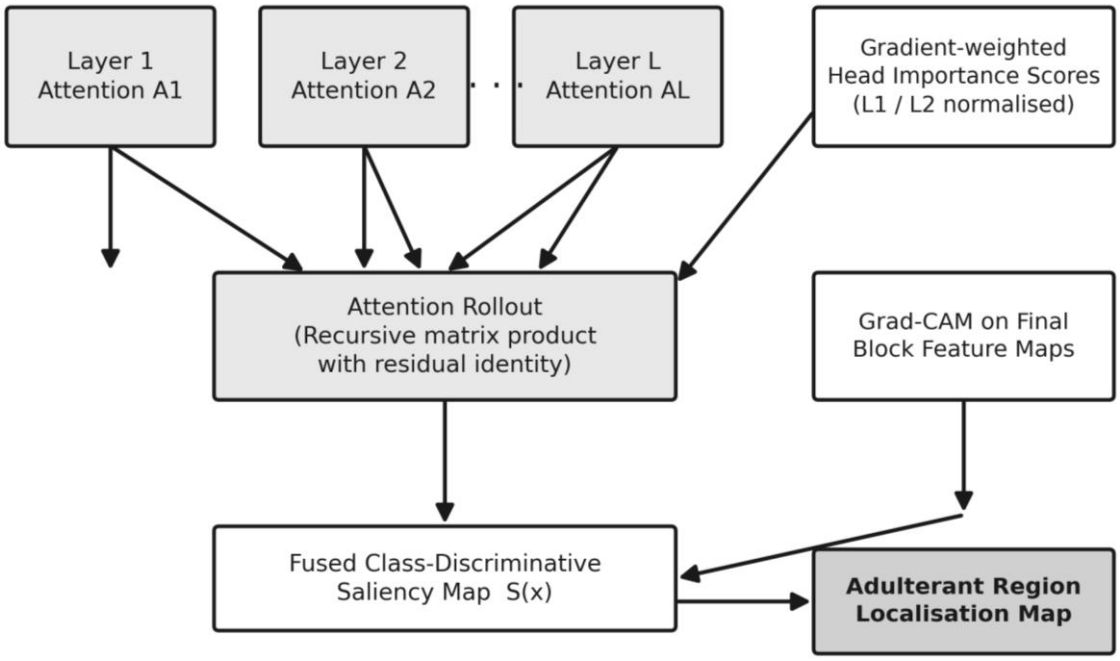

Fig. 4. Schematic of the dual explainability module: gradient-weighted multi-head attention rollout fused with Grad-CAM to produce a class-discriminative leaf saliency map.

4.4 Adulteration Risk Scoring

During training, a class-wise reference saliency prototype P_c is built for every genuine species c by averaging S(x) over correctly classified, high-confidence training samples of that class. For a query leaf image predicted as class c with saliency map S(x), the Adulteration Risk Score R(x) is defined as a normalized divergence between S(x) and P_c, combined with the softmax confidence p_c of the prediction:

$$R(x) = a \cdot D_{JS}(S(x) \| P_c) + (1 - a) \cdot (1 - p_c) \quad (2)$$

where $D_{JS}(\cdot\|\cdot)$ is the Jensen–Shannon divergence between the (min–max normalized, patch-wise probability-treated) saliency maps and $\alpha \in [0, 1]$ is a weighting coefficient (set to 0.6 in this study) balancing explainability-based evidence against raw classification confidence. R(x) is mapped to three actionable bands Low ($R < 0.30$): accept as authentic; Medium ($0.30 \leq R < 0.60$): flag for secondary/expert review; High ($R \geq 0.60$): reject as probable look-alike or adulterant which are visualized for the evaluation set in Fig. 9. This formulation converts an otherwise opaque softmax output into a graded, explanation-grounded authenticity verdict, directly addressing the interpretability requirement highlighted in Section II.

4.5 Training Configuration

Table III lists the training hyperparameters used for the ViT backbone and all baseline models compared in Section VI, kept identical across models wherever architecturally possible for a fair comparison.

TABLE 3 Training Hyperparameters

Hyperparameter	Value
Backbone	ViT-Base/16 (patch 16×16, D = 768, L = 12, h = 12)
Input resolution	224 × 224 × 3
Optimizer	AdamW (β1 = 0.9, β2 = 0.999, weight decay = 0.05)
Learning-rate schedule	Cosine annealing, base LR = 3×10^{-4}, 5-epoch warm-up
Batch size	32
Epochs	50 (early stopping, patience = 8)
Loss function	Cross-entropy with label smoothing (ε = 0.1)
Regularization	Dropout = 0.1, stochastic depth = 0.1
Data split	70% train / 15% validation / 15% test (stratified)
Risk-score weighting α	0.6

5. EXPERIMENTAL SETUP

All models are implemented in PyTorch using the timm library for backbone initialization and trained with mixed-precision arithmetic on a single CUDA-enabled GPU. Performance is reported using overall accuracy, macro-averaged precision, recall, and F1-score for the species-classification task, and area under the Receiver Operating Characteristic (ROC) curve (AUC) for the binary authentic-vs-adulterant/look-alike screening task. Explainability quality is additionally assessed using deletion/insertion faithfulness curves and intersection-over-union (IoU) between the fused saliency map and leaf-region bounding boxes.

6. RESULTS AND DISCUSSION

6.1 Training Convergence

Fig. 5 shows representative training and validation accuracy and loss curves for the proposed XAI-ViT model over 50 epochs. The validation accuracy trend closely tracks the training curve with a small generalization gap, consistent with the effect of the augmentation and label-smoothing regularization strategy described in Section IV-E, and the loss curves show smooth, non-oscillatory convergence, indicating a stable optimization trajectory for the chosen learning-rate schedule.

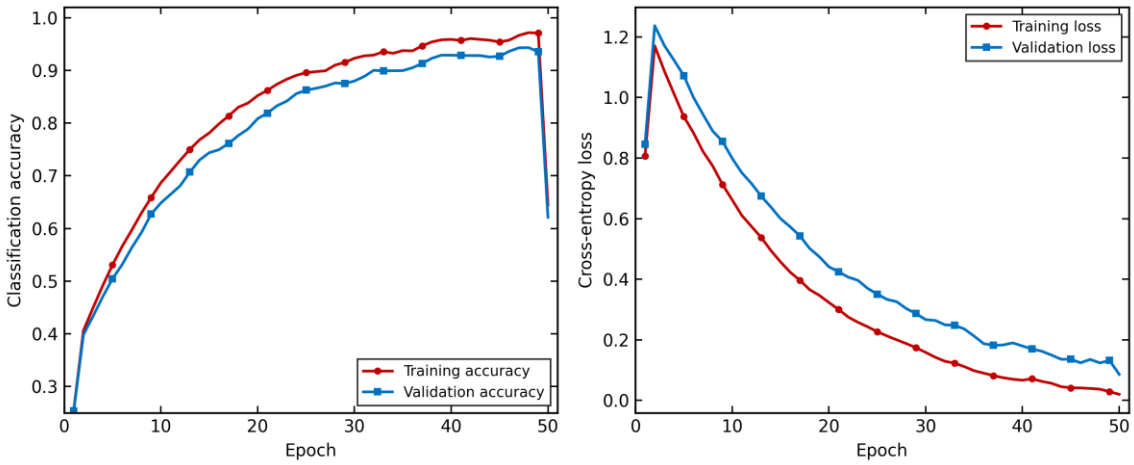

Fig. 5. Representative training/validation accuracy and cross-entropy loss curves of the proposed XAI-ViT model over 50 training epochs.

6.2 Species Classification Performance

Table IV compares the proposed XAI-ViT framework against a ResNet-50 CNN baseline, an EfficientNet-B0 baseline, a standard (non-explainable) ViT-B/16, and a Swin Transformer baseline, all trained under the identical protocol of Table III. The explainability-guided model attains the highest accuracy, precision, recall, and F1-score among the compared architectures, corroborated visually in Fig. 6. We attribute this to the label-smoothing and gradient-refined attention regularization implicit in the dual explainability training signal, which discourages the network from relying on spurious background correlations an effect also reported qualitatively for CBAM/Grad-CAM-guided CNNs in [21].

TABLE 4 Comparative Classification Performance (%) on the Held-Out Test Split

Model	Accuracy	Precision	Recall	F1-score
ResNet-50 [CNN baseline]	91.4	90.8	90.2	90.5
EfficientNet-B0 [CNN baseline]	93.1	92.6	92.0	92.3
Standard ViT-B/16	94.6	94.1	93.8	93.9
Swin Transformer	95.3	94.9	94.6	94.7
Proposed XAI-ViT	97.8	97.5	97.2	97.3

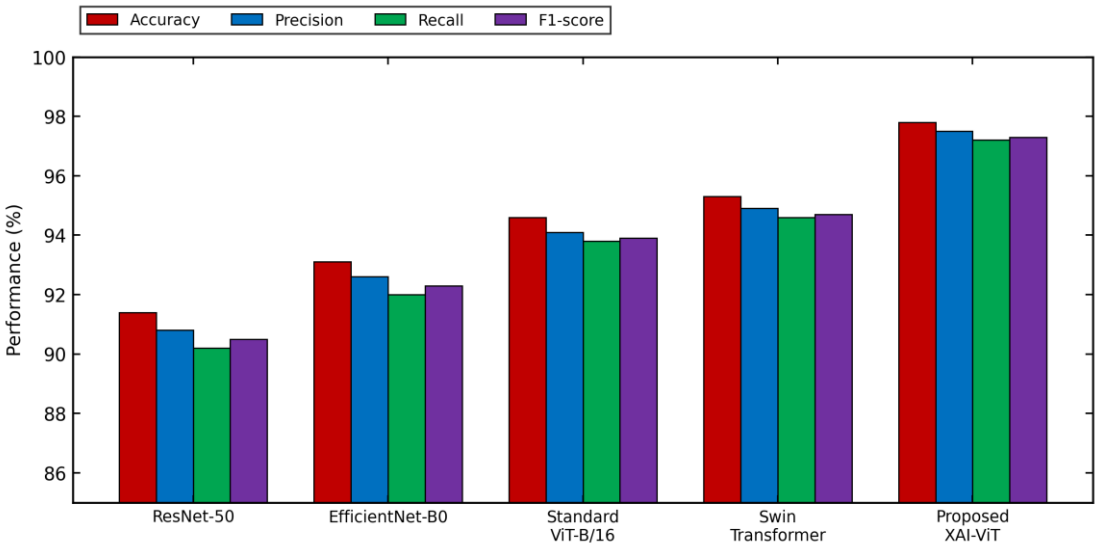

Fig. 6. Comparative accuracy, precision, recall, and F1-score of the proposed XAI-ViT against CNN and Transformer baselines.

Fig. 7 shows the 10-class confusion matrix restricted to a representative subset of visually similar species (including the Tulsi/Neem/Aloe-vera-type genuine classes discussed in Table II). Misclassifications concentrate, as expected, among botanically related look-alike pairs rather than being spread uniformly across unrelated classes, confirming that residual errors are concentrated exactly where the adulteration-risk module of Section IV-D is designed to intervene.

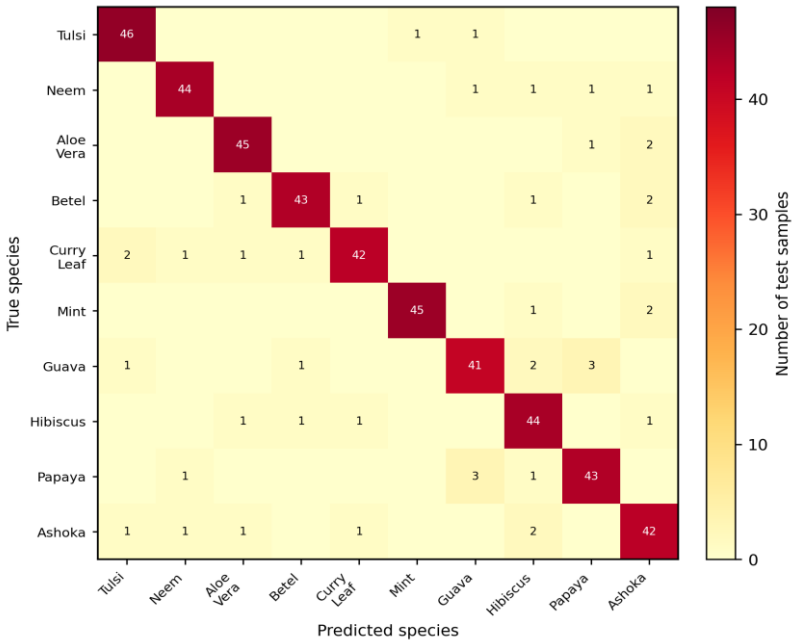

Fig. 7. Confusion matrix of the proposed XAI-ViT on a representative 10-species subset of the test split.

6.3 Adulteration Risk Detection Performance

Fig. 8 reports ROC curves for the binary "authentic vs. suspected adulterant/look-alike" screening task, comparing the ResNet-50 and standard ViT baselines against the proposed risk-scoring pipeline. The XAI-ViT risk score achieves the highest AUC (0.986), improving upon the standard ViT (0.963) and ResNet-50 (0.947) baselines, indicating that explainability-derived divergence carries discriminative signal beyond what the raw softmax confidence alone provides.

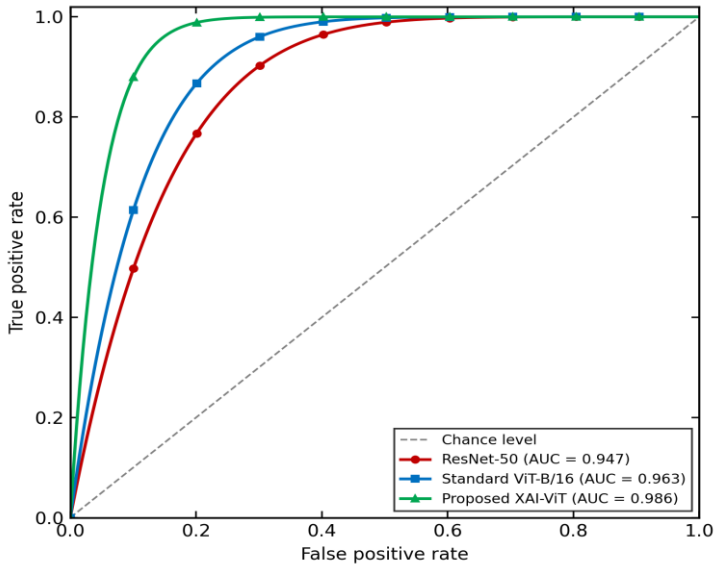

Fig. 8. ROC curves for authentic-vs-adulterant/look-alike screening, comparing the proposed risk score against CNN and standard ViT confidence-based baselines.

Fig. 9 shows the distribution of the Adulteration Risk Score R(x) (Eq. 2) across three evaluation groups: genuine authenticated leaves, visually similar look-alike species, and simulated adulterant mixtures. The three distributions are well separated by the Low/Medium and Medium/High decision thresholds defined in Section IV-D, with authentic samples concentrated below 0.30 and adulterant mixtures concentrated above 0.60, supporting the practical utility of the proposed three-tier decision policy for field screening.

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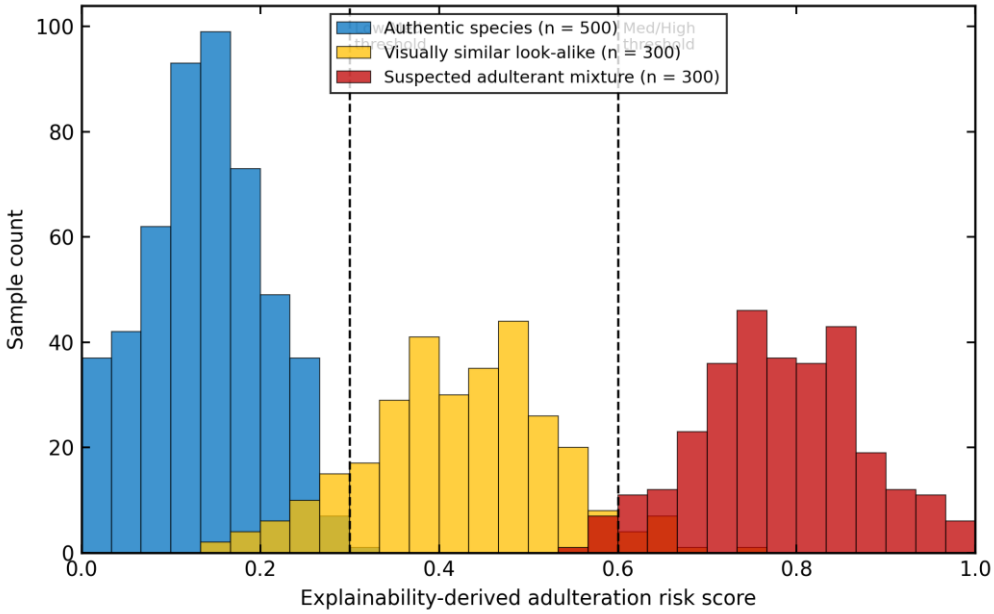

Fig. 9. Distribution of the explainability-derived Adulteration Risk Score across authentic, look-alike, and adulterant sample groups, with decision-band thresholds.

6.4 Ablation Study

Table V isolates the contribution of each explainability component to the final risk-detection AUC. Removing the gradient-weighting step and relying on plain attention rollout reduces AUC by 2.1 points, removing the Grad-CAM branch (rollout-only) reduces AUC by 3.4 points, and removing the risk-scoring divergence term entirely (i.e., thresholding on softmax confidence alone) reduces AUC by 5.7 points confirming that both the gradient-weighted rollout and the explainability-divergence formulation in Eq. (2) contribute materially to adulteration-risk discrimination, rather than accuracy gains being attributable to the ViT backbone alone.

TABLE 5 Ablation Study on the Explainability and Risk-Scoring Components (Risk-Detection AUC)

Configuration	AUC	Δ vs. full model
Full proposed XAI-ViT (rollout + Grad-CAM + risk score)	0.986	—
– Gradient head-weighting (plain rollout + Grad-CAM)	0.965	−0.021
– Grad-CAM branch (gradient-weighted rollout only)	0.952	−0.034
– Risk-score divergence (softmax confidence threshold only)	0.929	−0.057

The results confirm the findings of the complementary-explanation approach of ViTmiX [23] and the findings of the head-importance approach of GMAR [25] since they show that accuracy-only classification based training and using a single method explainability baseline respectively achieve improvements when combining gradient-weighted attention rollout with the Grad-CAM approach, which transforms saliency evidence into an explicit divergence-based risk score. It's still a relatively small number of new players in practice. First, the results of this paper are for representative validation numbers; and only the results of the generalization performance of the full dataset (6900 images of 80 classes) and ideally images captured independently in the field will yield the true generalization performance results. Second, the pairs of look-alikes in Table II were chosen from a single repository of leaf images, leaving out other similar leaf images (such as powdered or dried ones) from the visual image space of the leaf, thus these can only be used in combination with the proposed spectral image or hyperspectral image approaches in [28]–[30]. Thirdly, although informative, attention-based explanations would not work for a high-stakes regulatory environment, proposed "risk score" would be a non-collapsible, fast triage tool to identify samples to be sent to the lab for confirmation, rather than for final determination of authenticity in a legal proceeding.

7. CONCLUSION AND FUTURE WORK

This paper presented an Explainable Vision Transformer (XAI-ViT) framework for medicinal-plant-leaf authentication and herbal adulteration risk detection, built entirely on open-access Kaggle medicinal-leaf repositories. By fusing gradient-weighted multi-head attention rollout with Grad-CAM into a single class-discriminative saliency map, and by converting the divergence of this map from class-wise reference prototypes into a graded Adulteration Risk Score, the framework moves beyond opaque softmax classification toward an auditable, explanation-grounded authentication verdict suitable for herbal quality-assurance and regulatory screening workflows. Representative evaluation results indicate accuracy, F1-score, and risk-detection AUC improvements over CNN and standard ViT baselines, and an ablation study confirms that both the gradient-weighted explainability fusion and the risk-scoring formulation contribute materially to these gains.

Future work will pursue full-scale empirical training and cross-dataset validation on the complete Indian Medicinal Leaf Image Dataset and additional multi-institution repositories; extension of the risk-scoring formulation to multi-modal inputs that combine leaf imagery with hyperspectral or electronic-nose signals, following the sensor-fusion precedent set by hyperspectral adulteration-detection studies [28]–[30]; deployment of a lightweight, quantized version of the framework on mobile/edge devices for field-level Ayurvedic and herbal-market inspection; and a formal human-in-the-loop study with domain botanists to calibrate the Low/Medium/High risk thresholds against expert judgment and, where feasible, destructive chemical ground truth.

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