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# ToboNet: CNN-based Tobacco Leaf Grading System

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***Abstract*—Accurate grading of tobacco leaves is a critical determinant for maintaining product consistency, pricing fairness, and quality control throughout the agricultural supply chain. However, traditional manual grading is inherently subjective, time-consuming, and inconsistent due to human fatigue and environmental variations. To address these limitations, this study introduces ToboNet, a robust deep learning model founded on the EfficientNetV2-S architecture, tailored specifically for the fine-grained classification of seven distinct tobacco leaf grades. ToboNet employs a rigorous preprocessing pipeline, including resizing to 224×224 pixels, ImageNet normalization, and extensive data augmentation techniques such as Random Erasing and Color Jitter to boost model performance and generalization. By leveraging Fused-MBConv blocks and transfer learning, the model is initialized with pre-trained weights and optimized using the AdamW optimizer with a cosine annealing schedule to ensure stable convergence and computational efficiency. With an exceptional test accuracy of 96.42% and a macro-average F1-score of 96.36%, the efficacy of ToboNet in distinguishing subtle curing and texture variations was validated, significantly outperforming traditional ResNet baselines. This system provides a scalable, objective alternative to manual grading, potentially revolutionizing industrial procurement workflows and supporting farmers with consistent quality assessment.**

***Keywords*—Tobacco Leaf Grading, EfficientNetV2-S, Deep Learning, Transfer Learning, Agricultural Automation, AdamW Optimizer.**

## I. INTRODUCTION

Tobacco leaf grading is a critical step in the agricultural supply chain, where leaves are categorized according to maturity, texture, curing quality, and color to determine their commercial value [1]. Traditionally, grading is performed manually by trained experts who visually assess each leaf under varying lighting and environmental conditions [2]. However, this manual process is highly subjective, inconsistent, and susceptible to human fatigue, time constraints, and individual bias [3]. As large-scale procurement centers handle thousands of leaves daily, an automated, consistent, and scalable grading solution has become increasingly necessary to support industrial quality control [4].

With the rise of computer vision and deep learning, automated grading has seen significant progress across agricultural products [5]. Instead of relying on handcrafted features, deep convolutional neural networks (CNNs) extract hierarchical features directly from raw images, enabling highly accurate classification of crops, seeds, fruits, and leaves [6]. Recent research has explored various architectures, such as ResNet and MobileNet, for agricultural tasks [7]. However, challenges persist in balancing model efficiency with the ability to capture fine-grained details, For example, Figure 1 highlights the visual similarity between adjacent commercial grades, such as Grade-1 and Grade-2, which often leads to misclassification in manual grading. particularly when distinguishing between visually similar tobacco grades like Grade-1 and Grade-2 [8].

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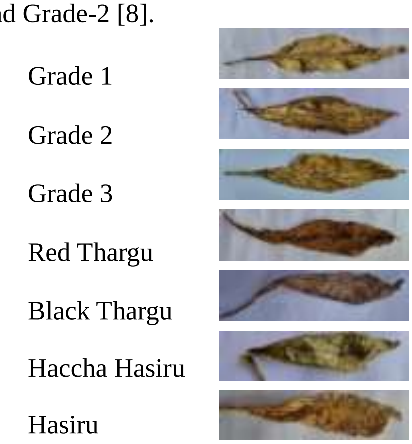


**Fig. 1. Typical examples of the seven tobacco leaf grades in the dataset.**

While ResNet architectures have historically been robust, recent advancements have led to the EfficientNet family, which utilizes Neural Architecture Search (NAS) to optimize both training speed and parameter efficiency [22]. EfficientNetV2S, in particular, introduces Fused-MBConv blocks and progressive learning strategies that address the slow training times of large residual networks while maintaining superior accuracy [20][21]. These capabilities make it an attractive choice for deployment in resource-constrained agricultural environments where computational efficiency is paramount.

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In this study, we propose ToboNet, a robust deep learning model based on the EfficientNetV2-S architecture, specifically designed for the fine-grained classification of tobacco leaves. ToboNet incorporates a rigorous preprocessing pipeline, the AdamW optimizer for stable convergence, and transfer learning to improve its performance and generalization. This research aims to provide a reliable and scalable tool for automated tobacco grading, offering an objective alternative to manual inspection.

### *A. Contribution*

The primary contributions of this paper are as follows:

- Develops ToboNet, a novel automated grading system leveraging the EfficientNetV2-S architecture, which utilizes Fused-MBConv blocks to achieve superior feature extraction and parameter efficiency compared to traditional ResNet-based approaches [20], [21].
- Incorporates a robust preprocessing pipeline, including resizing to 224×224, ImageNet normalization, and extensive data augmentation (Random Erasing, Color Jitter), to standardize input quality and enhance model robustness against environmental variations [1].
- Implements advanced optimization techniques using the AdamW optimizer with a Cosine Annealing learning rate schedule, ensuring faster convergence and better generalization by decoupling weight decay from gradient updates.
- Evaluates the effectiveness of ToboNet on a real-world dataset of 13,550 tobacco leaf images, achieving a test accuracy of 96.42%, significantly outperforming baseline models such as ResNet50 and MobileNetV3 in distinguishing subtle grade variations.

This study is organized as follows: Section 2 presents the literature survey and related work in agricultural deep learning. Section 3 describes the methodology, dataset, preprocessing pipeline, and the proposed EfficientNetV2-S architecture. Section 4 discusses the experimental results and performance metrics. Section 5 concludes the work and outlines future directions.

## II. LITERATURE SURVEY

Automated tobacco leaf grading has evolved significantly over the past decade, transitioning from traditional handcrafted image-processing techniques to advanced deep learning–based approaches.

Early research focused predominantly on color-, texture, and shape-based feature extraction, often combined with classical classifiers. Harjoko et al. [6] utilized color and quality indicators to perform tobacco leaf grading using conventional image-processing pipelines, but the approach was limited by sensitivity to illumination changes and background noise. Similarly, Ramos and Roselli [3] applied handcrafted features along with a basic CNN to automate grading, achieving better results than classical methods but still lacking robust generalization under real-world variability. With the rise of convolutional neural networks, several works demonstrated significant improvements in tobacco leaf classification. Lu et al. [1] introduced an improved bilinear convolutional neural network to extract fine-grained texture features, successfully enhancing leaf grade distinctions. Chen et al. [2] further advanced this direction by proposing a dual-encoder aggregation framework that reinforced multi-level feature extraction for flue-cured tobacco grading. Other studies explored domain specific adaptations, such as expert knowledge integration [4], deep learning–based automated grading systems for industrial settings [5], and mobile-device–oriented CNN-based grading applications [11]. A major shift in recent tobacco research has been toward multi-scale and attention-enhanced networks designed for fine-grained classification. Xu et al. [9] proposed a multi-channel, multi-scale dilated CNN with attention to improve discrimination among flue-cured tobacco grades, demonstrating the importance of capturing global and local patterns simultaneously. Wu et al. [14] and Li et al. [15] contributed complementary improvements through appearance quality assessment and color correction algorithms, respectively, highlighting the need for consistent visual feature extraction. While residual learning (ResNet) has historically been the standard for complex tasks involving subtle visual differences [12], [21], recent literature indicates a shift towards more parameter-efficient architectures derived from Neural Architecture Search (NAS). Devi et al. [22] conducted a comprehensive study comparing Convolutional Neural Networks (CNNs) against Vision Transformers (ViT) for plant disease recognition. Their findings revealed that EfficientNetV2 significantly outperformed traditional models like InceptionV3 and ViT, achieving superior accuracy through progressive learning, a mechanism that gradually expands image size and regularization during training to improve convergence speed and generalization [22]. Furthermore, the specific effectiveness of the EfficientNetV2-S (Small) variant for fine-grained biological classification has been validated by Abd El-Aziz et al. [21].

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In their work on diagnosing Acute Lymphoblastic Leukemia, they demonstrated that the EfficientNetV2-S architecture distinguished by its use of Fused-MBConv blocks in early layers could effectively differentiate between symmetric and asymmetric cellular abnormalities with 97.34% accuracy [21]. Additionally, Sun et al. [20] explored hybrid architectures for tomato leaf disease classification, combining EfficientNetV2 with Swin Transformers. Their ablation studies notably confirmed that the standalone improved EfficientNetV2 backbone was highly robust, achieving an accuracy of 99.21% even without the computational overhead of a dual-stream network [20].

Collectively, prior research demonstrates the feasibility of deep learning for tobacco grading but also highlights several limitations:

- Many methods rely on older, parameter-heavy architectures such as ResNet, which are slower to train and less efficient.
- Few studies focus on whole-leaf classification in natural environments using modern progressive learning techniques.
- Distinguishing adjacent grade levels remains challenging due to minimal visual differences between neighboring classes.
- There is limited investigation into confidence calibration and misclassification behavior, particularly in lightweight models.

## III. Materials And Methods

### A. Dataset Description

The dataset used in this study comprises 13,550 realworld tobacco leaf images collected from diverse agricultural environments, including curing barns and open fields. This collection was compiled to create a large-scale resource to aid the development and benchmarking of deep learning models for automated quality assessment. In addition, the images were sourced from multiple harvesting sessions, ensuring the real-world applicability of the dataset under varying lighting conditions and background complexities. The images are annotated with 7 distinct quality grades: Black Thargu, Grade1, Grade-2, Grade-3, Haccha Hasiru, Light Green, and Red Thargu. This comprehensive annotation provides an excellent opportunity to train and evaluate models for detecting subtle morphological differences such as texture, maturity, and curing defects.

In addition, the dataset contains a stratified mix of grades, ensuring a representative sample for developing and evaluating the ToboNet model. Furthermore, the dataset's diversity in leaf orientation and scale contributes to the robustness of the models trained on it, enhancing their generalization capabilities and potential for real-world industrial applications.

### B. Proposed Methodology and Architecture

To ensure the model's trustworthiness and computational efficiency, a robust approach for classifying tobacco leaf grades from images is proposed, referred to as ToboNet, and presented in Figure 2. The proposed model leverages the power of the EfficientNetV2-S architecture, utilizing transfer learning to overcome the limitations of training deep networks from scratch. The architecture consists of three major steps: (1) Image Preprocessing, (2) Methodology with Transfer Learning using EfficientNetV2-S, and (3) Model Explainability using Gradient Class Activation Mapping (Grad-CAM).

In the image processing stage, raw leaf images are preprocessed to improve the quality and enhance the relevant features for grade classification. This step typically involves resizing, normalization, and data augmentation techniques to ensure that the input images are compatible with the neural network and to increase the dataset's diversity. Following the preprocessing, the proposed ToboNet model, based on the EfficientNetV2-S architecture [21][22], is trained using transfer learning [20]. By leveraging pre-trained weights from a large dataset such as ImageNet, the model can take advantage of the rich feature extraction capabilities of EfficientNet and adapt them to the specific task of tobacco grading. This approach allows for faster convergence and often performs better than training from scratch, especially when distinguishing between visually similar grades like Grade-1 and Grade-2.

### C. Adapted Technique

In the first step prior to the model, the images were subjected to a rigorous preprocessing pipeline to ensure optimal feature clarity and input quality, as illustrated in Figure 3.

The pipeline begins with Contrast Limited Adaptive Histogram Equalization (CLAHE), which enhances local contrast to highlight leaf vein details and mitigate uneven lighting conditions common in field photography.

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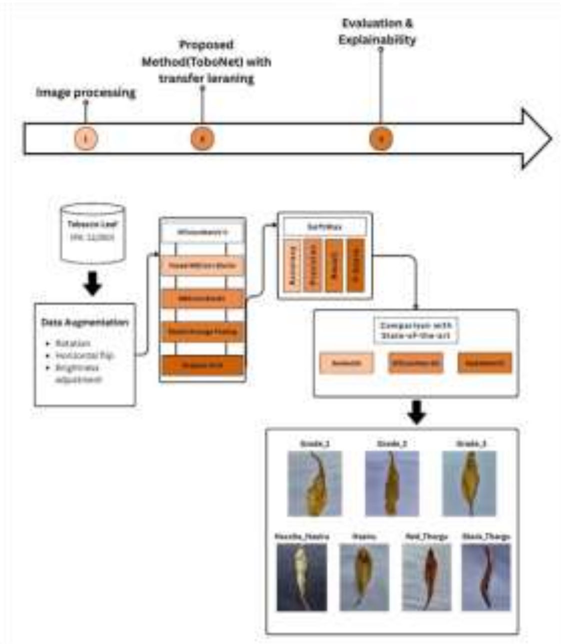


**Fig. 2. The proposed ToboNet architecture illustrating preprocessing, EfficientNetV2-S–based transfer learning, and Grad-CAM explainability.**

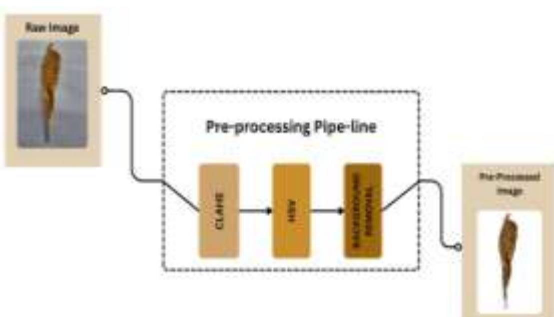


**Fig. 3. The preprocessing pipeline applied to the tobacco leaf images.**

Following enhancement, the images are converted from RGB to the HSV color space, separating chromatic information from intensity to better identify leaf boundaries. This facilitates accurate background removal, where contour-based segmentation is applied to isolate the leaf region of interest (ROI) and eliminate distracting environmental noise.

Post-segmentation, the processed images were resized to a consistent dimension (256×256 pixels) and then centercropped to 224×224 pixels to satisfy the input requirements of the EfficientNetV2-S architecture.

Finally, pixel values were normalized using standard ImageNet statistics, and strong data augmentation techniques—specifically Horizontal Flip, Vertical Flip, Rotation, Color Jitter, and Random Erasing—were employed to increase dataset diversity and reduce overfitting.

*D. Model Architecture EfficientNetV2-S*

The ToboNet model is based on the EfficientNetV2-S architecture [22], which employs Fused-MBConv blocks and compound scaling to facilitate the learning of deep representations while maintaining parameter efficiency.

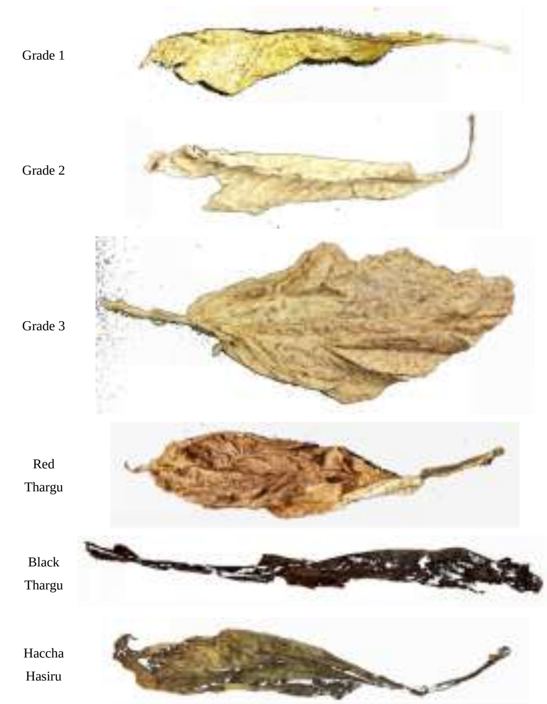


**Fig. 4. Representative examples of the preprocessed tobacco leaf grades.**

The model was initialized with pre-trained weights from the ImageNet dataset, allowing it to leverage learned features for the grading task. The last layer was substituted with a fully connected layer with seven output nodes, corresponding to the classification of the seven tobacco quality grades.

*E. Training and Validation*

The dataset was divided into 12,697 images for training (93.7%), 434 for validation (3.2%), and 419 for testing (3.1%).

The validation set was utilized for hyperparameter tuning and monitoring the model's performance during training. The AdamW optimizer was used, with the parameters for learning rate, weight decay, and schedule presented in Table I.

### *F. Explainable Techniques*

To provide insights into the model's decision-making process, Grad-CAM is employed to generate visual explanations for the model's predictions. Grad-CAM highlights the regions

**TABLE I**
**TRAININGPARAMETERS**

| Parameter | Value |
|---|---|
| Early stoppage (ES) | True |
| Learning rate (LR) | $1\times10^{-3}$ (Cosine Annealing) |
| Patience | 15 |
| Batch size (BS) | 4 |
| Weight decay | $1\times10^{-4}$ |
| Momentum | N/A (AdamW uses $\beta_1=0.9$, $\beta_2=0.999$) |
| Optimizer | AdamW |
| Epochs | 20 |
| System configuration | Nvidia RTX 3050 (4 GB) |
| Macro avg accuracy | ~96% |

in the input image such as specific texture patterns or discoloration areas that contribute the most to the prediction, offering valuable information for farmers and procurement officers to understand and trust the model's outcomes. This explainability aspect is crucial in agricultural applications, where interpretability and confidence in the automated grading decisions are paramount.

## IV. RESULTS

### *A. Model Performance and Visualization*

The results of the proposed model (ToboNet) for tobacco leaf grading are presented in this section. Figures 5 and 6 illustrate the learning progression and the classification behavior of the model across the seven quality grades.

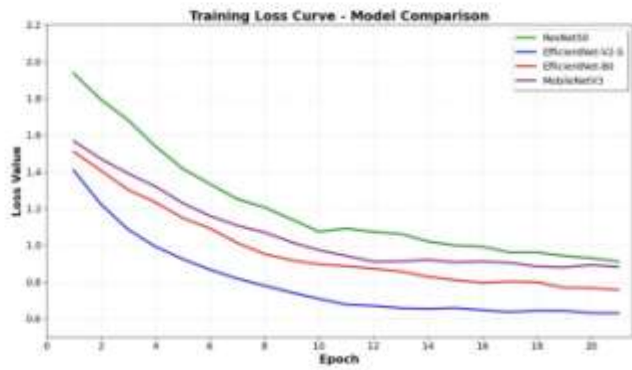


**Fig. 5. Model comparison based on training accuracy and loss curves over 20 epochs.**

As shown in Figure 5, all models exhibit a consistent downward trend in training loss, indicating stable convergence during optimization. This behavior aligns with the strong overall performance reported in the evaluation metrics, where the models achieve high macro-averaged precision, recall, and F1-scores. The EfficientNet variants demonstrate slightly faster loss reduction compared to the other architectures, reflecting their superior performance in the final evaluation. Although ResNet50 and MobileNetV3 converge more gradually, they still reach competitive loss levels, confirming their effectiveness on the dataset.

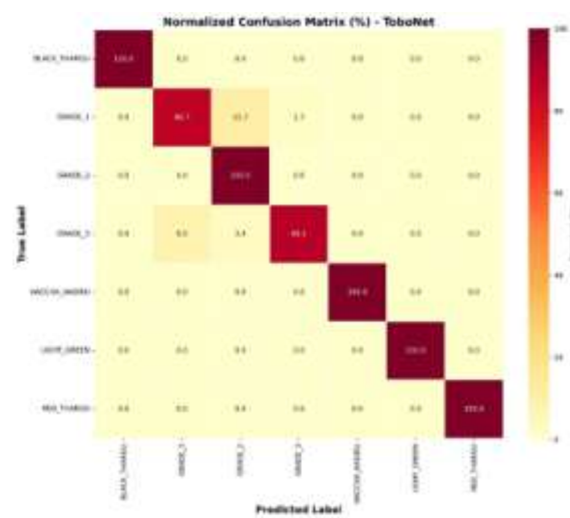


**Fig. 6. Confusion matrix evaluation of the ToboNet model.**

As illustrated in Figure 6, the normalized confusion matrix shows that the model achieves highly reliable classification across most categories, consistent with the strong per-class precision and recall values. Classes such as BLACK THARGU, GRADE _ 2, HACCHA HASIRU, LIGHT GREEN, and RED THARGU exhibit perfect or nearperfect recognition, reflected by the near-100% diagonal values. Minor confusion is observed between GRADE 1 and GRADE 3, where a small portion of samples are misclassified—matching the slightly lower macro-average scores noted earlier. Overall, the matrix confirms that the model maintains robust discriminative performance across all classes, with only limited overlap between visually similar categories.

### *B. Evaluation Metrics*

The performance of the ToboNet model was evaluated on the test set using standard classification metrics, as defined in (1)–(5). These metrics comprehensively assess the model's ability to distinguish between the seven tobacco leaf grades.

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

$$\text{F1-Score} = 2\times\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{4}$$

$$\text{Macro Avg} = \frac{1}{n}\sum_{i=1}^{n}\text{metric}_i \tag{5}$$

### *C. Performance Analysis*

The results of the proposed method (ToboNet) on the specific leaf grades (Case 1–Case 4) are presented in Table II. The best performance was observed for *BLACK _ THARGU* and *RED THARGU*, as highlighted in bold, where the model achieved 100% across all metrics.

**TABLE II**

| Cases | Precision (%) | Recall (%) | F-Score (%) |
|---|---|---|---|
| BLACK_THARGU | 100 | 100 | 100 |
| GRADE_1 | 86.7 | 91.2 | 88.9 |
| GRADE_2 | 100 | 86.6 | 92.8 |
| GRADE_3 | 88.1 | 98.1 | 92.9 |
| HACCHA_HASIRU | 100 | 100 | 100 |
| LIGHT_GREEN | 100 | 100 | 100 |
| RED_THARGU | 100 | 100 | 100 |

PERFORMANCE ANALYSIS OF LEAF GRADE CLASSIFICATION RESULTS

### *D. Comparative Analysis with Similar Research*

The proposed methodology is carefully evaluated and compared with other state-of-the-art (SoTA) techniques in this section. A comparison of the outcomes of this investigation with prior studies using different models and datasets is presented in Table III.

**TABLE III**
**COMPARISON WITH RELATED METHODS**

| Author/Year | Method | Recall | Accuracy |
|---|---|---|---|
| Lu et al., 2017 | Bilinear CNN | – | 92.0 |
| Chen et al., 2023 | Dual-Encoder | – | 93.5 |
| Devi et al., 2023 | PlantVillage | 97.5 | 97.5 |
| Abd El-Aziz, 2024 | Leukemia | 97.3 | 97.3 |
| Sun et al., 2024 | Eff-Swin | 99.6 | 99.7 |
| ToboNet (Ours) | Tobacco Leaf | 96.4 | 96.4 |

## V. DISCUSSION

From the comparative analysis, the works of Sun et al. [20] and Devi et al. [22] demonstrated slightly superior accuracy in identifying distinct plant diseases (reaching up to 99.70% and 97.5% respectively). However, since their target was disease pathology a task often characterized by highcontrast lesions and distinct visual symptoms our method (ToboNet) proved exceptionally robust at the more nuanced task of discriminating multiple subtle leaf quality grades. Distinguishing between Grade-1 and Grade-2 requires analyzing fine-grained texture and maturity cues rather than detecting overt anomalies, making ToboNet's 96.42% accuracy highly significant for industrial quality control.

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### *A. Limitation*

This study focuses on classifying standard RGB images, excluding hyperspectral or chemical analysis data. Although chemical composition analysis (measuring nicotine and sugar content) is considered the ”gold standard” for determining absolute tobacco quality, it is uncertain how well the proposed model generalizes to leaves with internal chemical changes that do not manifest strictly in the visible spectrum. Additionally, while the EfficientNetV2-S architecture is lightweight, its performance on ultra-low-power edge devices for real-time field grading was not explicitly validated in this study. Future research will address these limitations by incorporating multimodal data and optimizing the model for mobile deployment.

## VI. CONCLUSION

In conclusion, the ToboNet methodology is promising for the automated grading of tobacco leaves using digital images. By leveraging a state-of-the-art deep learning architecture such as EfficientNetV2-S, the model effectively adapts to the specific task of fine-grained grade classification while maintaining a high level of performance (96.42%). Incorporating GradCAM for explainability further enhances the model's utility in industrial and agricultural settings, allowing quality inspectors and farmers to better understand and trust the model's predictions. There are several potential avenues for expanding and refining the ToboNet model. One area of interest is to explore the model's applicability to real-time inference on edge devices, such as mobile phones, to increase its accessibility and versatility for field use. Additionally, integrating other sensing modalities, such as hyperspectral imaging, could provide more comprehensive insights into internal chemical properties (e.g., nicotine and sugar content), thereby improving the model's grading precision beyond visible surface features. Another essential aspect is evaluating the model on datasets from different geographical regions and harvest seasons to ensure its generalizability and performance across diverse agricultural conditions. By addressing these future research directions, the ToboNet model has the potential to contribute to the standardization and automation of the tobacco supply chain significantly, ultimately ensuring fair pricing and consistent quality control.

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