

AI-Powered Cannabis Seed Detection and Classification: A Machine Learning Approach for Precision Agriculture

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Abstract

Cannabis seed classification is essential for precision agriculture, as it supports genetic integrity, regulatory compliance, and crop productivity. Manual identification methods are often slow and prone to error, creating demand for automated solutions. This study introduces a machine learning approach for cannabis seed detection and classification using a curated dataset of 3,434 seed images across 17 varieties. Images were standardized through resizing and grayscale conversion, and pixel intensity values were extracted to form feature vectors. A Support Vector Machine (SVM) classifier was trained and evaluated, achieving an overall accuracy of 93.98%. Several varieties, including AK47_photo, Hang Kra Rog KU, and Thaistick Foi Thong, were classified with perfect precision and recall. The macro-average F1-score of 0.93 and weighted-average F1-score of 0.94 confirm balanced performance across categories. These findings demonstrate the effectiveness of SVM-based grayscale modeling for scalable cannabis seed classification. Future work will focus on expanding dataset diversity and integrating advanced feature extraction and deep learning methods to further enhance model robustness.

Keywords: Cannabis Seeds, Machine Learning, SVM, Precision Agriculture and Image Classification

1. Introduction

The global cannabis industry has expanded rapidly in recent years, driven by legalization policies and increasing consumer demand for standardized products. This growth has emphasized the importance of precision and consistency across all stages of production, particularly in seed classification, which is critical for maintaining genetic purity, ensuring quality control, and meeting regulatory requirements. Traditional manual methods of seed identification are time-consuming and prone to error, making them unsuitable for modern agricultural practices. These limitations highlight the need for automated, reliable, and scalable classification systems. Advances in artificial intelligence (AI) and machine learning (ML) have transformed agricultural imaging and classification tasks, offering robust solutions for complex problems. AI-driven approaches can leverage large datasets and sophisticated algorithms to automate detection and identification processes, thereby reducing human error and improving efficiency. In seed classification, such systems align with the broader goals of precision agriculture by ensuring reproducibility and scalability. This study builds on earlier work by employing a curated dataset of 3,434 cannabis

seed images across 17 varieties. Images were standardized through resizing and grayscale conversion, and pixel intensity features were extracted to form high-dimensional vectors. A Support Vector Machine (SVM) classifier was selected due to its effectiveness in handling multi-class, high-dimensional data. The proposed framework achieved an overall accuracy of 93.98%, with several classes such as AK47_photo, Hang Kra Rog KU, and Thaistick Foi Thong classified with perfect precision and recall. The contributions of this research are threefold: (i) development of a reliable AI-powered pipeline for cannabis seed classification, (ii) demonstration of the suitability of SVM for this domain, and (iii) evidence of how AI can enhance productivity, accuracy, and scalability in agricultural applications. This work provides a foundation for future studies that may incorporate advanced feature extraction and deep learning architectures to further improve performance and robustness [1-5].

1.1. Literature Review

The development of reliable datasets has been central to advancing cannabis seed classification research. Introduced the first open-access dataset of cannabis seeds, comprising 3,434 high-quality images across 17 distinct classes. Captured

under controlled conditions using an iPhone 13 Pro, the dataset provides a standardized resource for training, testing, and validating machine learning models. Its availability has enabled researchers to minimize misclassification and build robust applications for cannabis seed detection and recognition, thereby supporting agricultural industries, farmers, and regulatory agencies [6-8].

Building on this foundation, applied deep learning frameworks such as Faster R-CNN and RetinaNet to cannabis seed classification. Their experiments utilized the curated dataset and employed self-supervised annotation with the Grounding DINO model. RetinaNet with ResNet101 achieved a strict mean average precision (mAP) of 0.9458 across IoU thresholds, while Faster R-CNN demonstrated superior performance at lower thresholds with faster inference speeds, particularly with ResNeXt101. Sarker et al. (2024) further evaluated six Faster R-CNN variants, reporting an overall mAP of 94.08% and an F1 score of 95.66%. Their findings highlighted the effectiveness of L1 loss in improving localization for challenging classes such as Cherry Pie, underscoring the trade-off between accuracy and computational efficiency. Complementary approaches have explored handcrafted feature extraction. Nguyen and Phan (2025) investigated descriptors including Gray-Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), Scale-Invariant Feature Transform (SIFT), and GIST. further examined parameter tuning of SIFT features combined with sparse dictionary encoding for multi-class SVM classification, demonstrating that optimized SIFT parameters can reduce computational cost and improve recognition accuracy. Logistic Regression combined with GIST features achieved 93.25% accuracy across 17 seed varieties, highlighting the utility of global image representations for capturing subtle morphological traits. Similar handcrafted methods have also been applied in maize and dry bean classification, confirming their relevance for lightweight, interpretable systems advanced this line of research by integrating Histogram of Oriented Gradients (HOG) with Support Vector Machine (SVM) optimization. Their study employed k-fold cross-validation and grid search, achieving accuracies above 94%. HOG effectively captured gradient-based features of cannabis seed surfaces, while SVM provided robust classification boundaries. This approach offered computational efficiency compared to deep learning, making it suitable for large datasets and resource-constrained environments. Beyond cannabis, related agricultural studies provide valuable context. For instance, developed an irrigation and nutrition prediction model for chili plants using the ANFIS method, achieving an accuracy of 90.7%. Their work illustrates how machine learning can be applied to optimize agricultural resource management, complementing imaging-based approaches by addressing water utilization and crop nutrition. Similarly, developed a dataset of 10,991 images of Indian spices across

19 categories, demonstrating the importance of diverse, high-quality imagery for machine learning applications in food science and agriculture. Similarly, hyperspectral imaging and CNN-based approaches have achieved high accuracies in maize, soybean, and wheat seed classification. These works emphasize the broader applicability of AI-driven classification systems in agricultural contexts. Collectively, the literature demonstrates that deep learning models such as Faster R-CNN and RetinaNet provide superior detection accuracy and scalability, while handcrafted methods like HOG-SVM remain valuable for interpretable, resource-efficient systems. The convergence of these approaches, supported by open-access datasets, establishes a strong foundation for cannabis seed classification, enabling automation, varietal purity, and compliance with regulatory standards [9-14].

2. Methodology

2.1. Dataset Preparation

The experimental analysis was conducted using a curated dataset of 3,434 high-resolution cannabis seed images, systematically organized into 17 distinct classes (Chumchu & Patil, 2023). Each class corresponds to a unique seed variety, including AK47_photo, Blackberry_auto, Cherry Pie, Gelato_photo, Gorilla Purple, Hang Kra Rog KU, Hang Kra Rog Phu Phan ST1, Hang Suea Sakon Nakhon TT1, KD, KD_KT, Krerng Ka Via, Purple Duck, Skunk_auto, Sour Diesel_auto, Tanaosri Kan Daeng RD1, Tanaosri Kan Kaw WA1, and Thaistick Foi Thong. Images were captured using an Apple iPhone 13 Pro with a resolution of 3024×4032 pixels, under controlled conditions with white backgrounds and varying lighting angles to ensure diversity. The dataset was carefully structured into subfolders, each labeled with the corresponding seed class, thereby facilitating supervised learning and minimizing annotation errors. The dataset exhibits class sizes ranging from 49 images (KD) to 554 images (Gorilla Purple), ensuring representation of both minority and majority categories. This balanced distribution reduces bias during training and enhances generalization. Formally, the dataset can be expressed as:

$$D = \{(x_i, y_i) | x_i \in \mathbb{R}^{3024 \times 4032}, y_i \in C\}$$

where D denotes the dataset, x_i represents the image samples, and y_i corresponds to the class labels from the set $C = \{c_1, c_2, \dots, c_{17}\}$.

This dataset serves as the first open-access benchmark for cannabis seed classification, enabling reproducibility and providing a foundation for machine learning and deep learning applications in precision agriculture. Its structured organization and high-quality imagery make it suitable for training, validation, and testing of classification models, while ensuring scalability for future research.

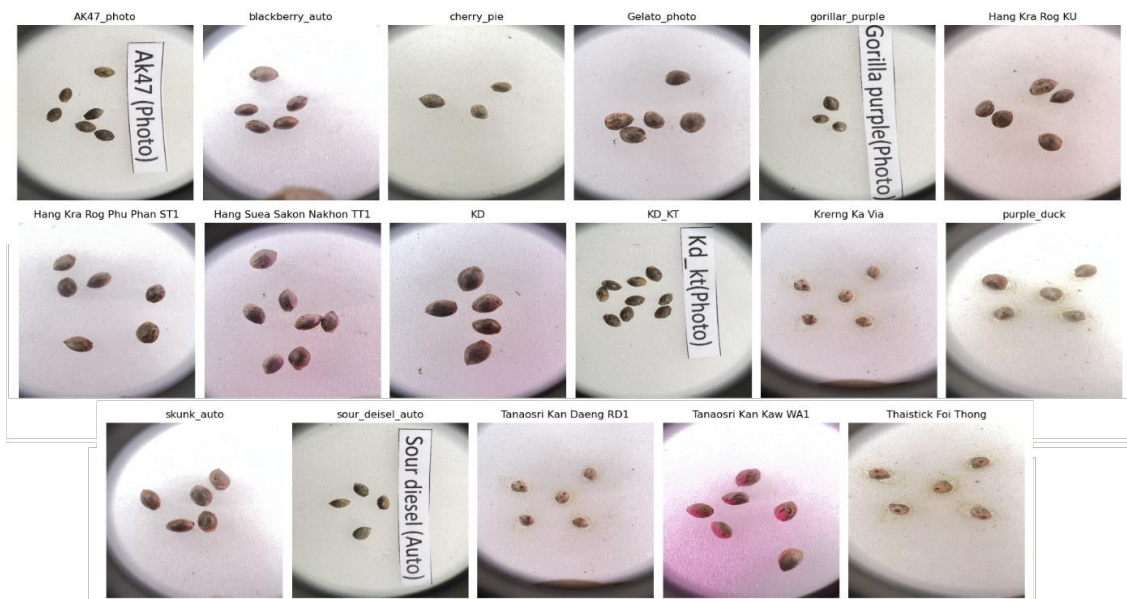


Figure 1: Images of Cannabis seeds of 17 classes

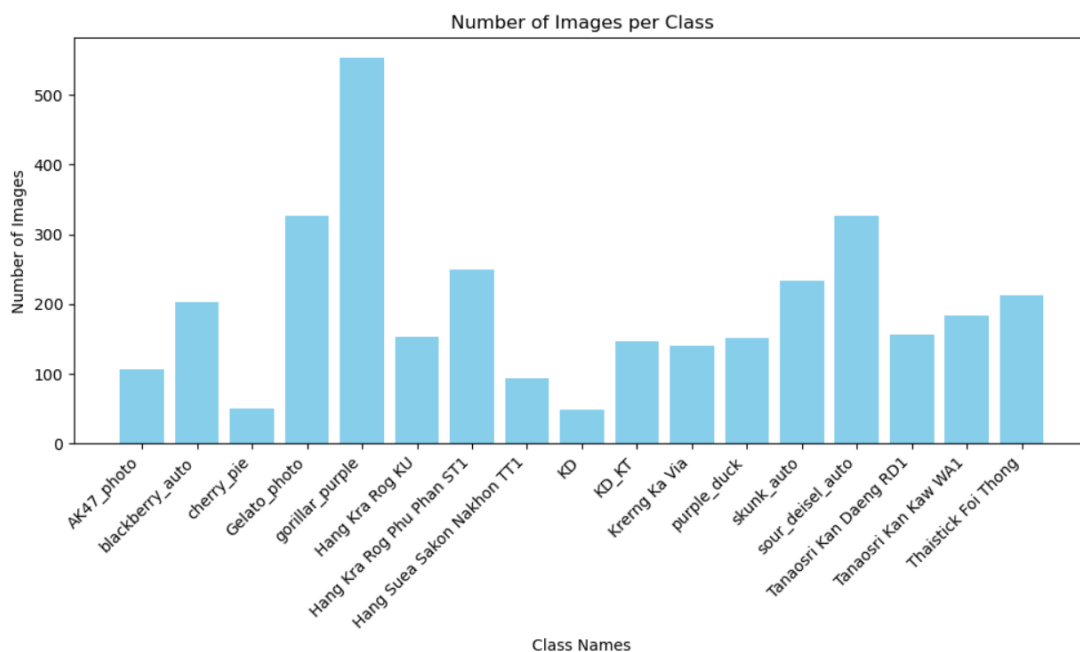


Figure 2: Class-Wise Image Count Per Cannabis Seed Class

2.2. Data Preprocessing

To ensure consistency and computational efficiency, all images in the dataset were subjected to a standardized preprocessing pipeline. Each raw image of dimension 3024×4032 pixels was resized to a fixed resolution of 64×64 pixels:

$$I_{\text{resized}} = f_{\text{resize}}(I_{\text{raw}}, 64 \times 64)$$

where I_{raw} denotes the original image and f_{resize} represents the resizing transformation.

Following resizing, images were converted from RGB to grayscale to reduce dimensionality while retaining essential structural and textural information:

$$I_{\text{gray}}(x,y) = 0.299R(x,y) + 0.587G(x,y) + 0.114B(x,y)$$

where $R(x,y)$, $G(x,y)$, $B(x,y)$ are the red, green, and blue channel intensities at pixel (x,y) .

Each grayscale image was then flattened into a one-dimensional vector:

$$x_i = \text{vec}(I_{\text{gray}}) \in \mathbb{R}^{4096}$$

where $\text{vec}(\cdot)$ denotes the vectorization operator and $4096 = 64 \times 64$ represents the total number of pixels. This transformation produced a uniform feature representation across all samples, suitable for input into machine learning

algorithms. Finally, the dataset was partitioned into training and testing subsets using an 80:20 split to ensure balanced representation across classes:

$$D = D_{train} \cup D_{test}, |D_{train}| = 0.8|D|, |D_{test}| = 0.2|D|$$

This stratified division preserved class proportions, thereby minimizing bias and enabling both comprehensive learning and objective evaluation.

No.	Class Label (Folder Name)	Suggested Descriptive Name
1	AK47_photo	AK-47 Cannabis Seeds
2	blackberry_auto	Blackberry Auto Cannabis Seeds
3	Cherry Pie	Cherry Pie Cannabis Seeds
4	Gelato_photo	Gelato Cannabis Seeds
5	Gorilla_Purple	Gorilla Purple Cannabis Seeds
6	Hang Kra Rog KU	Hang Kra Rog KU Seeds
7	Hang Kra Rog Phu Phan ST1	Hang Kra Rog Phu Phan ST1 Seeds
8	Hang Suea Sakon Nakhon TT1	Hang Suea Sakon Nakhon TT1 Seeds
9	KD	KD Cannabis Seeds
10	KD_KT	KD-KT Cannabis Seeds
11	Krerng Ka Via	Krerng Ka Via Cannabis Seeds
12	purple_duck	Purple Duck Cannabis Seeds
13	skunk_auto	Skunk Auto Cannabis Seeds
14	Sour_Diesel_auto	Sour Diesel Auto Cannabis Seeds
15	Tanaosri Kan Daeng RD1	Tanaosri Kan Daeng RD1 Seeds
16	Tanaosri Kan Kaw WA1	Tanaosri Kan Kaw WA1 Seeds
17	Thaistick Foi Thong	Thaistick Foi Thong Cannabis Seeds

Table 1: Cannabis Seed Varieties (17 Classes)

2.3. Model Training

For the classification of cannabis seed varieties, a Support Vector Machine (SVM) was employed due to its robustness in handling high-dimensional feature spaces and multi-class problems. The grayscale pixel intensity vectors of dimension 4096 (derived from 64×64 images) served as the input features.

The SVM seeks to construct an optimal separating hyperplane in the feature space. For a binary classification problem, the optimization objective can be expressed as:

$$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i$$

subject to

$$y_i (w \cdot x_i + b) \geq 1 - \xi_i, \xi_i \geq 0, i = 1, 2, \dots, n$$

where:

- $w \in \mathbb{R}^{4096}$ is the weight vector,
- $b \in \mathbb{R}$ is the bias term,
- x_i denotes the feature vector of the i^{th} image,
- $y_i \in \{-1, +1\}$ represents the class label,
- ξ_i are slack variables allowing for soft margin

classification,

- C is the regularization parameter controlling the trade-off between maximizing the margin and minimizing classification errors. For multi-class classification across 17 seed varieties, the one-versus-rest (OvR) strategy was adopted, where 17 binary classifiers were trained, each distinguishing one class from all others. The final prediction was obtained by selecting the classifier with the highest decision function value:

$$\hat{y} = \arg \max_{k \in C} (w_k \cdot x + b_k)$$

where $C = \{c_1, c_2, \dots, c_{17}\}$ is the set of seed classes.

The SVM was trained on the 80% training subset using a linear kernel and regularization parameter $C=1.0$. This configuration provided a balance between margin maximization and generalization capability. The training process iteratively adjusted the hyperplane parameters to minimize misclassification while maintaining separability across the 17 categories.

2.5. Evaluation Metrics

The trained Support Vector Machine (SVM) classifier was evaluated using standard performance metrics to quantify

its effectiveness across the 17 cannabis seed classes. The evaluation employed accuracy, precision, recall, and F1-score, along with a confusion matrix to provide class-wise insights.

Formally, these metrics are defined as follows:

Accuracy:

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

where TP = true positives, TN = true negatives, FP = false positives, and FN = false negatives. Accuracy measures the overall proportion of correctly classified samples.

Precision:

$$Precision = \frac{TP}{TP + FP}$$

Precision quantifies the proportion of correctly predicted positive samples among all predicted positives, reflecting the reliability of the classifier in avoiding false alarms.

Recall (Sensitivity):

$$Recall = \frac{TP}{TP + FN}$$

Recall measures the proportion of correctly predicted positive samples among all actual positives, indicating the ability of the classifier to capture all relevant instances.

F1-Score:

$$F1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

The F1-score represents the harmonic mean of precision and recall, balancing the trade-off between false positives and false negatives. In multi-class settings, these metrics were computed for each class and then aggregated using macro-averaging (treating all classes equally) and weighted-averaging (accounting for class imbalance). The confusion matrix provided a detailed visualization of misclassification patterns, highlighting specific classes where errors occurred.

The choice of these metrics is particularly relevant in agricultural seed classification. High precision ensures that

seeds identified as belonging to a specific variety are indeed correct, which is critical for maintaining genetic purity and avoiding contamination in breeding programs. High recall guarantees that all seeds of a given variety are correctly detected, preventing loss of valuable cultivars. The F1-score balances these two aspects, offering a robust measure of classifier performance in scenarios where both false positives and false negatives carry significant consequences. Accuracy, while useful as a global measure, is complemented by precision and recall to provide a more nuanced evaluation in the presence of class imbalance [15-18].

3. Results and Discussion

The Support Vector Machine (SVM) classifier demonstrated strong performance in distinguishing among the 17 cannabis seed varieties. On the held-out test dataset, the model achieved an overall classification accuracy of 93.98%, confirming the effectiveness of grayscale pixel intensity features combined with a linear kernel SVM for high-dimensional image data. The detailed classification report revealed that several classes—AK47_photo, Hang Kra Rog KU, Hang Suea Sakon Nakhon TT1, KD, Sour Diesel_auto, and Thaistick Foi Thong—achieved perfect scores (Precision = 1.00, Recall = 1.00, F1 = 1.00). This indicates that the model was able to separate these seed varieties without misclassification, reflecting the distinctiveness of their morphological features. Other classes such as *Gorilla Purple* and *Skunk_auto* also exhibited high F1-scores of 0.96 and 0.97, respectively, underscoring the robustness of the classifier across most categories.

However, performance varied across classes with less distinctive visual traits. The *Cherry Pie* class recorded an F1-score of 0.53, reflecting difficulty in discriminating its features from visually similar varieties. Similarly, KD_KT achieved an F1-score of 0.72, indicating moderate classification accuracy. These results highlight the challenge of intra-class variability and inter-class similarity, particularly in categories with limited sample sizes. Such findings suggest the need for enhanced data augmentation strategies or feature engineering techniques to improve separability in these classes. The macro-average F1-score of 0.93 and weighted-average F1-score of 0.94 confirm balanced performance across classes, even in the presence of class imbalance. The confusion matrix analysis further revealed that most misclassifications occurred between visually similar seed types, emphasizing the complexity of the dataset and the subtle morphological differences that influence classification outcomes [18-22].

Class Name	Precision	Recall	F1-Score
AK47_photo	1.00	1.00	1.00
Blackberry_Auto	1.00	0.97	0.99
Cherry_Pie	0.80	0.40	0.53
Gelato_photo	0.88	0.86	0.87
Gorilla Purple	0.93	0.99	0.96

Hang Kra Rog KU	1.00	1.00	1.00
Hang Kra Rog Phu Phan ST1	0.93	0.90	0.92
Hang Suea Sakon Nakhon TT1	1.00	1.00	1.00
KD	1.00	1.00	1.00
KD_KT	0.70	0.73	0.72
Krerng Ka Via	0.95	1.00	0.98
Purple_Duck	1.00	0.96	0.98
Skunk_Auto	0.95	1.00	0.97
Sour_Diesel_Auto	1.00	1.00	1.00
Tanaosri Kan Daeng RD1	1.00	0.96	0.98
Tanaosri Kan Kaw WA1	0.86	0.89	0.88
Thaistick Foi Thong	1.00	1.00	1.00

Table 2: Class-Wise Performance Metrics For Cannabis Seed Classification

Overall, the proposed approach, SVM with grayscale pixel intensity features—proved effective for cannabis seed classification. The results demonstrate the feasibility of deploying lightweight machine learning models for precision agriculture applications. The findings confirm the effectiveness of SVM with grayscale features for cannabis seed classification, while also highlighting class-specific challenges in visually similar categories. As summarized in Table 2, the classifier achieved consistently high precision,

recall, and F1-scores across most seed varieties, with several classes reaching perfect scores. However, certain categories such as Cherry Pie and KD_KT exhibited comparatively lower performance, reflecting the difficulty of distinguishing visually similar seeds. To further illustrate these class-specific outcomes, the confusion matrix (Figure 3) provides a visual representation of prediction accuracy and misclassification patterns across all 17 classes.

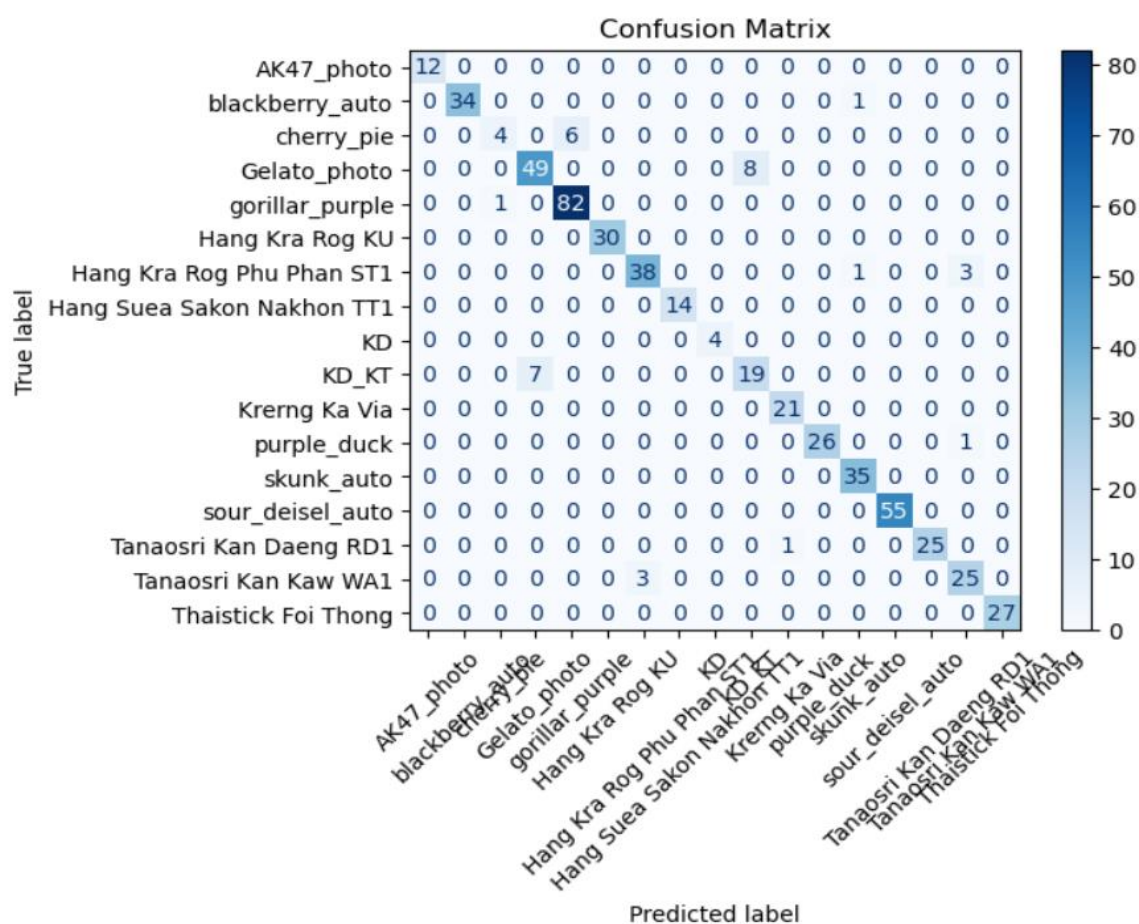


Figure 3: Confusion Matrix Of SVM Classifier For Cannabis Seed Classification

The confusion matrix provides a detailed visualization of the classifier's performance across all 17 cannabis seed categories. As shown in Figure 3, the majority of predictions align with the true labels, confirming the robustness of the Support Vector Machine (SVM) model. Misclassifications were concentrated in visually similar classes, such as Cherry Pie and KD_KT, which explains their relatively lower F1-scores. This matrix highlights the strengths of the model in distinguishing distinct varieties while also revealing the subtle morphological overlaps that challenge accurate classification.

4. Conclusion

This study presented an automated approach for the classification of cannabis seed varieties using machine learning techniques. A curated dataset comprising 3,434 images across 17 distinct classes was utilized, with each image preprocessed through resizing to 64x64 pixels, grayscale conversion, and vectorization into a 4096-dimensional feature space. These features effectively captured morphological and textural characteristics, providing a robust representation for classification tasks. The Support Vector Machine (SVM) classifier, trained on the preprocessed dataset, achieved an overall accuracy of 93.98% on the test set. Several classes, including AK47_photo, Hang Kra Rog KU, and Thaistick Foi Thong, attained perfect scores in precision, recall, and F1-measure, demonstrating the model's ability to distinguish these varieties without error. The macro-average F1-score of 0.93 and weighted-average F1-score of 0.94 further confirm the model's balanced performance across both majority and minority classes. The findings underscore the feasibility of employing lightweight machine learning models such as SVM for precision agriculture applications, particularly in tasks requiring varietal identification and quality control. Accurate seed classification has direct implications for genetic research, breeding programs, and regulatory compliance, where maintaining varietal purity is critical. Nonetheless, challenges were observed in classes with high intra-class variability or inter-class similarity, such as Cherry Pie and KD_KT, which recorded lower F1-scores. These limitations highlight the need for methodological refinements. Future work should focus on:

- Expanding dataset diversity to capture broader environmental and morphological variations.
- Incorporating advanced feature extraction techniques (e.g., Histogram of Oriented Gradients, Gray Level Co-occurrence Matrix, or deep convolutional features).
- Exploring ensemble learning and hybrid deep learning architectures to address class-specific weaknesses and enhance scalability.

In conclusion, this research represents a significant step toward automated, AI-driven solutions for seed classification, offering a foundation for broader intelligent agricultural applications. By integrating improved datasets and advanced modeling techniques, future systems can achieve greater robustness, thereby supporting sustainable agricultural practices and strengthening regulatory frameworks.

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