Innovative Food Technologies 13(1) (2025) 61-71

Iranian Research Organization for Science and Technology (IROST)

Innovative Food Technologies

journal homepage: https://jift.irost.ir

Analyzing the performance of deep learning models in tea fraud detection: A case study of black tea

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ARTICLE INFO

Keywords:
Tea,
Fraud,
Deep learning,
Model performance

ABSTRACT

Tea is not only among the most popular beverages worldwide but also a vital agricultural product, valued for its health benefits and diverse industrial applications. However, tea fraud remains a major challenge in the industry, involving practices such as the addition of foreign materials and artificial colors, or the falsification of geographical origin, all of which can negatively impact consumer health. At present study, two deep learning models, namely EfficientNet and Swin Transformer, were evaluated for their ability to detect three types of fraud in Iranian black tea: tea waste, low-quality foreign tea, and expired tea. The results indicated that the EfficientNet model achieved higher accuracy in detecting tea waste, whereas the Swin Transformer model demonstrated superior performance in identifying foreign tea and expired tea. The overall accuracy of the EfficientNet and Swin Transformer models was 88.5% and 77.6% for detecting tea waste, 85% and 83% for detecting foreign tea, and 61.3% for both models in detecting expired tea. However, further optimization of the model settings is recommended to reduce errors and improve performance.

1. Introduction

Tea has been used as a traditional beverage for health promotion and mental relaxation since its inception, and contains compounds with antioxidant, anti-inflammatory, immune-enhancing, metabolic regulator, and cell-protective properties [1,2]. New applications of tea span multiple industries, including the pharmaceutical sector with the development of epigallocatechin gallate (EGCG) capsules for cancer treatment [3], the cosmetic industry for anti-aging products [4], nanotechnology for nanoparticle synthesis [5], and the food industry for weight-loss supplements [6]. Tea is also one of the most important agricultural products worldwide, making a significant contribution to the export revenues and income generation of producing countries [7].

Food adulteration is generally defined as the international addition of substandard substances or components to a product for profit, which can pose risks to consumer health [8]. The prevalence of adulteration in herbs and spices, coffee and tea, and fruits and vegetables has accelerated, emphasizing the need for comprehensive regulatory frameworks and effective enforcement mechanisms to ensure the authenticity and integrity of these products [9]. Adulteration of black tea is a particular problem due to its widespread global consumption. As a pure beverage, black tea should be free from foreign substances, added coloring agents, and other harmful substances [10]. Tea adulteration has become a major problem in the tea industry, involving the addition, mixing, or packaging of adulterated substances to increase product volume or create a false impression of higher value. Color and appearance are key attributes that not only influence consumers' purchasing decisions but also play a crucial role in determining the value of tea products [11].

Key factors contributing to tea fraud include the substantial price disparity-reaching up to 300%-between high-quality and ordinary tea, the high cost of producing premium tea, weak regulatory systems in nearly 60% of tea-producing countries, and insufficient coordination between national and international standards. Fraud can be classified into four main categories: (1) physical fraud, such as the addition of leaves from other plants (up to 40% by volume) or tea waste and dregs [12]; (2) chemical fraud, involving artificial colors, flavors, or caffeine [13]; (3) geographical fraud, which falsifies the origin, such as Darjeeling or Fujian white tea, or the timing of leaf harvest [14]; and (4) biological fraud, including the use of non-standard species of the main tea plant [15].

Several analytical methods are used to detect tea fraud, including traditional methods [16-19], DNA-based approaches [20-22], spectroscopic techniques

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DOI: http://dx.doi.org/10.22104/ift.2025.7831.2232
(Received: 20 August 2025, Received in revised form: 20 September 2025, Accepted: 27 September 2025)
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[23,24], chromatographic methods [25,26], and emerging technologies based on machine learning and artificial intelligence [27].

Artificial intelligence and machine learning play a key role in detecting tea fraud by analyzing complex datasets and identifying unusual patterns. The data required to train artificial intelligence models is collected from various sources. In the next step, data preprocessing is performed, including noise removal, data normalization, and key feature extraction. Then, a suitable machine learning model -either supervised or unsupervised- is selected. Model training then involves optimization, evaluation, and measurement of data against desired criteria.

Convolutional neural networks (CNN) are widely regarded as one of the most effective methods in tea fraud detection due to their high ability to process images and automatically extract features. By analyzing tea images, these networks are able to accurately identify adulteration with plant waste, artificial colors, or impurities.

A review of the literature suggests that although traditional diagnostic techniques such as DNA, spectroscopy, and chromatography show high accuracy and sensitivity in monitoring food quality, they have limitations such as time-consuming, sample destruction, high cost, and the need for expert personnel. Therefore, an innovative solution is to develop an automated machine vision system for food quality monitoring that overcomes the limitations of traditional methods by offering rapid, non-destructive, cost-effective, and user-friendly analysis without requiring expert personnel. The present study aimed to identify three types of tea fraud - tea waste, expired tea, low-quality foreign tea- using image processing and machine learning based on two deep learning algorithms.

2. Material and methods

2.1. The study area

Black tea in northern Iran, especially in Gilan province, is of high quality and diversity due to specific climatic conditions (i.e., high humidity, acidic soil, and adequate rainfall). The main types of black tea produced in this region are: premium black tea (grade 1) which includes buds, whole and young leaves, second-grade black tea containing broken leaves with a dark brown color, pen tea from middle-quality whole leaves, and black tea leaves from Khakeh (grade 3).

In the present study, 2 kg of premium Iranian black tea was obtained from a tea processing factory in Lahijan, Gilan, Iran (37°12′26″N; 50°00′14″E). This factory complies with the national standard for black tea, which specifies the physical and chemical characteristics of pure black tea and is approved by the National Standards Organization of Iran. In order to train the automated system for tea adulteration detection, three common types of adulteration in the tea industry, namely tea waste, expired tea, and low-quality foreign tea, were mixed with the tea under study.

The types of frauds and their mixing percentages with the original tea are shown in Table 1. Initially, for each of the three types of adulteration (i.e., tea waste, foreign tea, and expired tea), four classes were defined based on the mixing levels of 0%, 15%, 45%, and 100%. From each class, 200 images were obtained, resulting in a total of 800 images (4 classes × 200 images) for each type of adulteration. In total, the dataset used in this study comprised 2,400 images. To ensure a uniform sample volume across all classes, a frame measuring 25 × 35 × 5 cm was prepared. The measured sample was placed into the frame, evenly spread to achieve a homogeneous layer, and the frame was then carefully removed. Then, RGB images of all samples were taken using a Canon digital camera (EF-S 18-55 mm, 24.1 megapixels). The camera settings were as follows: shutter speed 1/25 s, focal length 25-35 mm, aperture f/1.8, and ISO 250. The images were taken without flash, using laboratory lighting, which was kept constant in all photos. For digital parameters, images were captured at a resolution of 4000 × 1800 pixels, with a depth of 8 bits per pixel per channel, in RGB format, using the camera's JPEG format with a low compression ratio. The camera was positioned vertically above the samples using a fixed holder at a distance of 20 cm. The sample number and class type were noted next to the sample (Fig.2.), and the same procedure was followed for all other comparisons. Finally, the images were manually cropped one by one to remove the background (Fig.3.). These images were randomly divided into three distinct groups-training, validation, and testing-with a ratio of 6:2:2, which were equally distributed by class.

Table 1. Portion of adulterated tea (P1, P2 and P3) mixing with the original tea (A) in the present study

Class	0%	15%	45%	100%
Mixing A+P1	A (100%)	P1 (15%) +A (85%)	P3 (45%) +A (55%)	P1 (100%)
Mixing A+P2	A (100%)	P2 (15%) +A (85%)	P3 (45%) +A (55%)	P2 (100%)
Mixing A+P3	A (100%)	P3 (15%) +A (85%)	P3 (45%) +A (55%)	P3 (100%)

Fig. 1. Example of a tea sample preparation image

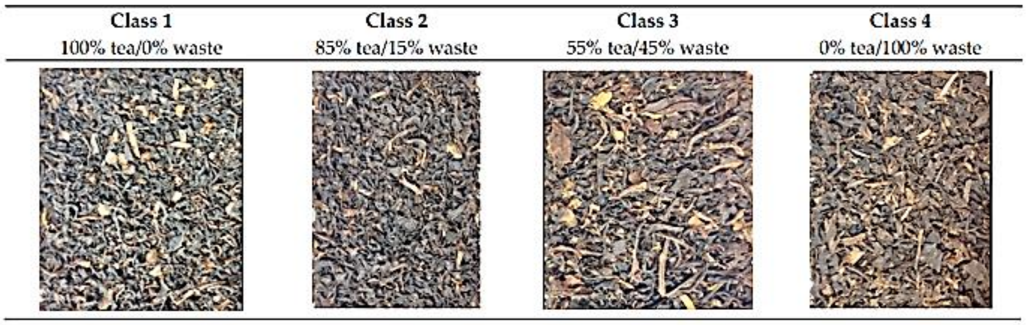

Fig. 2. Examples of different tea classes, i.e. 0%, 15%, 45% and 100%, to identify frauds

2.1. Methodology

The original resolution of the images was 1320 × 880 pixels, which resized to 660 × 440 pixels to reduce the memory shortage problem. The images were introduced in 3D (width × height × channel) in the models. The training, validation, and testing of the models were implemented in the Google Cloud environment using a Tesla T4 GPU (NVIDIA, Santa Clara, CA, USA).

2.1.1. Proposed classifiers for detection of tea adulteration

Two classifiers were used to classify the images in the dataset: EfficientNet and Swin Transformer. Both models were trained using a batch size of 10. The cyclic learning rate scheduler was used to update the learning rate after each step. In this paper, each step is the application of one training or validation batch to the model. The scheduler was of type “triangular2” which starts from a value of base_lr=$10^{\wedge -4}$ and linearly increases the learning rate up to the specified max_lr =0.4 and repeats the same process downward to complete a cycle. After each cycle, the values of base_lr and max_lr are halved until training is finished. The cycle size of the scheduler is 10,000 and 5000 for the models, respectively. The SGD optimizer was used to train the models for 200 epochs.

2.1.1.1. EfficientNet

There are two versions of the EfficientNet model, v1 (1D) and v2 (2D). EfficientNet v1 achieves ideal performance across a wide range of tasks by simultaneously scaling the depth, width, and resolution of the network while maintaining computational efficiency. However, training and fine-tuning the model can be computationally expensive and time-consuming due to its larger size and complexity, especially when training larger images [28]. EfficientNet v2 improves on its predecessor by introducing a new scaling method called random depth and an improved hybrid scaling method that focuses on improving training speed and accuracy. In this study, the version of EfficientNet v2 was used.

2.1.1.2. Swin Transformer

Swin Transformer is a novel hierarchical architecture that introduces windows to efficiently capture local and global dependencies in images [29]. This model also has two versions, v1 and v2. The Swin v1 Transformer (called Swin v1T) achieves improved performance on various image recognition tasks and outperforms previous architectures such as vision transformer. The Swin v2Transformer builds on the success of its predecessor by addressing three key challenges in training large vision models: (1) training instability, (2) resolution gap, and (3) reliability of labeled data. The version of Swin v2 Transformer (Swin V2T) was used in this study.

2.2. Evaluating the performance of classifiers in tea adulteration detection

Various criteria are used to evaluate the performance of the classifier. The first category is the

criteria related to the confusion matrix including recall, accuracy, precision, and F-score [30].
The confusion matrix is a tool used in machine learning, especially in classification tasks. This matrix helps to visualize the performance of a classification model by summarizing the number of correct and incorrect predictions. The values of TP, FP, TN, and FN are shown in Table 2 for the current case study with 4 classes.

Table 2. The values for $TP1$, $FP1$, $TN1$ and $FN1$ for a case with 4 classes

		Predicted Label			
		Class1	**Class2**	**Class3**	**Class4**
Real Label	Class1	TP		FN	
	Class2				
	Class3	FP		TN	
	Class4				

Accuracy indicates the overall accuracy of the model's predictions based on the target value, which is the percentage of the system's total correct responses (Eq 1).

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \times 100 \qquad (1)$$

Precision indicates the positive predictions of the model. In the case of multi-class classification, we calculate the accuracy of each class separately and the average of all classes (Eq 2).

$$= \frac{TP_i}{TP_i+FP_i} Precision_{\,i} \qquad (2)$$

Recall (sensitivity) measures the model's ability to find all positive samples (Eq 3).

$$= \frac{TP_i}{TP_i+FN_i} Recall_{\,i} \qquad (3)$$

The F-score or represents the harmonic mean of the precision and recall scores (Eq 4).

$$= \frac{2 \times Precision_i \times Recall_i}{Precision_i+Recall_i} F1 - score_{\,i} \qquad (4)$$

TP is the number of samples in each class that are correctly classified. TN is the number of samples on the main diagonal of the disturbance matrix minus the number of samples that are correctly classified in the class of interest. FP is defined as the sum of the horizontal samples of the class under consideration minus the number of samples that are correctly classified in the class of interest; it is the sum of the vertical samples of the class under consideration minus the number of samples that are correctly classified in the class of interest.

3. Results and discussion

3.1. Model size and training time in detecting tea adulteration

Table 3 shows the overall comparison between the proposed models based on model size and training time in detecting adulteration mixed with tea. Based on the data in Table 3, the EfficientNetV2S model is significantly lighter (smaller model size) and in most cases faster than the SwinV2T model. The larger size of the SwinV2T model is due to its transformer-based architecture and larger number of parameters, which naturally requires a longer training time. This difference is especially evident in the detection of "foreign tea" (P2), where the training time of SwinV2T is approximately 6.5 times that of EfficientNetV2S.

This finding indicates a key trade-off between performance and computational cost. In applications that require real-time processing or implementation on resource-constrained hardware (such as edge devices), the EfficientNetV2S model is a much more desirable option due to its smaller size and higher speed. In contrast, if maximum accuracy is the main goal and there are no computational resource constraints, larger models such as SwinV2T can be a good option

Table 3. The comparison of models regarding model size and training time in detecting tea adulteration

Models	**Model Size (Mb)**	**Training Time (s)**	**Adulteration**
EfficientNetV2S	77.578	5.855	Tea Waste (P1)
SwinV2T	105.626	9.081	
EfficientNetV2S	77.578	5.855	Foreign Tea (P2)
SwinV2T	105.626	*37.8*	
EfficientNetV2S	*78.9*	*19.8*	Expired Tea (P3)
SwinV2T	*103..2*	*28.6*	

3.2. Evaluation of proposed classifiers in detecting tea adulteration

3.2.1. EffecientNet classifier

The graphs of loss-train-validation and accuracy-train-validation of proposed classifiers are given in Fig. 3. According to figure, in tea waste detection (P1), the model shows fast and stable convergence. The validation error decreases rapidly and the accuracy reaches a high value, indicating successful learning of the discriminative visual patterns. In contrast, for foreign tea (P2) and especially expired tea (P3), the validation accuracy plot exhibits significant fluctuations. These fluctuations, especially in P3, could indicate the difficulty of the model in learning.

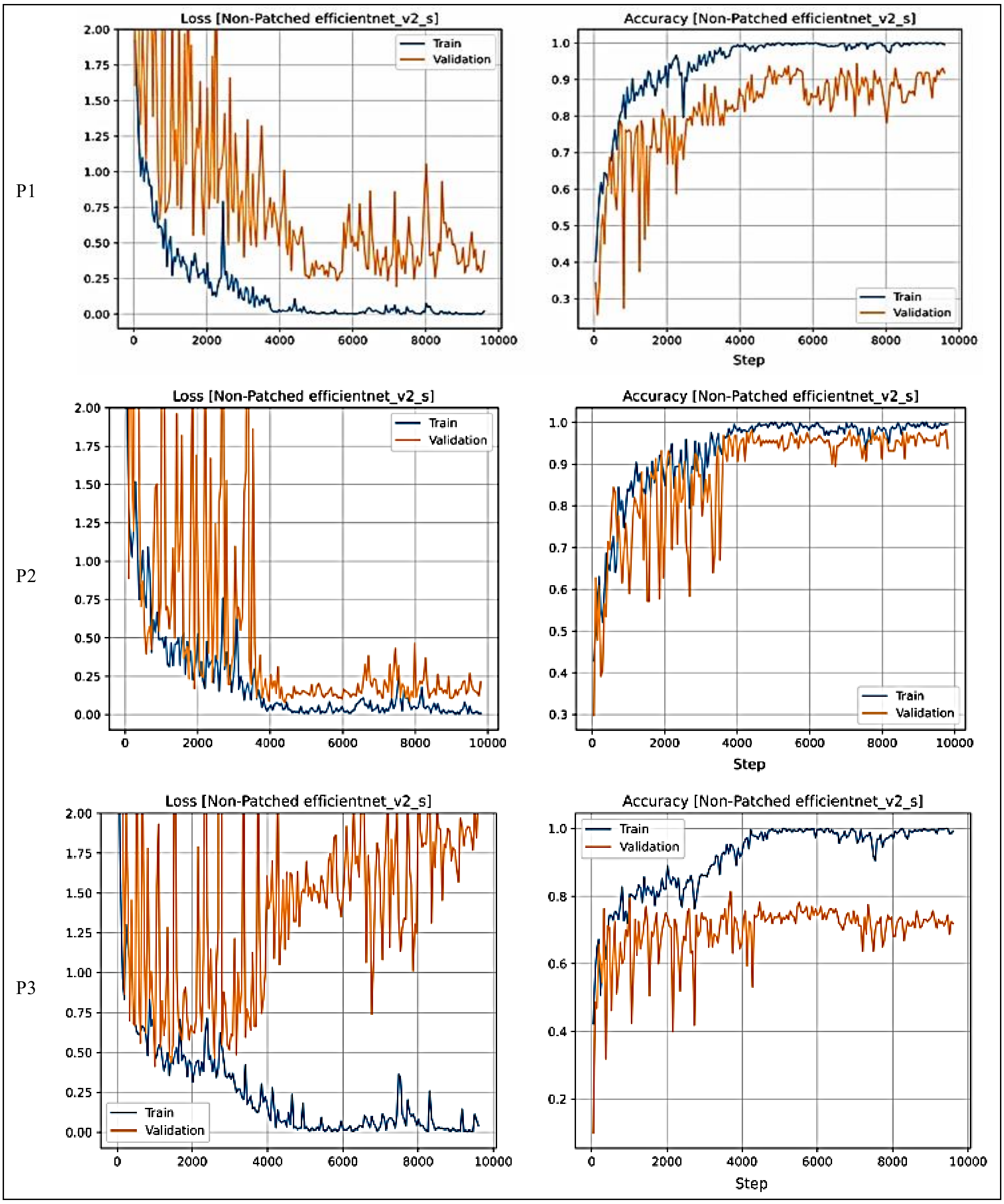

Fig. 3. Loss-train-validation and accuracy-train-validation of EffecientNet classifiers in detection of tea adulteration; P1: Tea waste, P2: Foreign Tea, P3: Expired tea

The confusion matrix of the EfficientNet classifier for detecting tea adulteration are shown in Fig. 4. For tea waste (P1), the values on the main diameter of the matrix are very high and the values outside the diameter are close to zero. This confirms that the model has a high accuracy in distinguishing tea leaves from healthy tea. For foreign tea (P2), the number of prediction errors (values outside the diameter) increases, indicating a relatively lower accuracy of the model in this task. The performance in detecting expired tea (P3) shows an intermediate state between P1 and P2; that is, its accuracy is lower than P1 but better than P2.

The superior performance of EfficientNet in detecting tea waste (P1) can be attributed to the nature of its architecture, which is based on convolutional neural networks (CNN). CNNs are very powerful in extracting local features such as texture, edges, and fine patterns. Tea leaves probably have a unique texture and grain pattern that the model can effectively recognize.

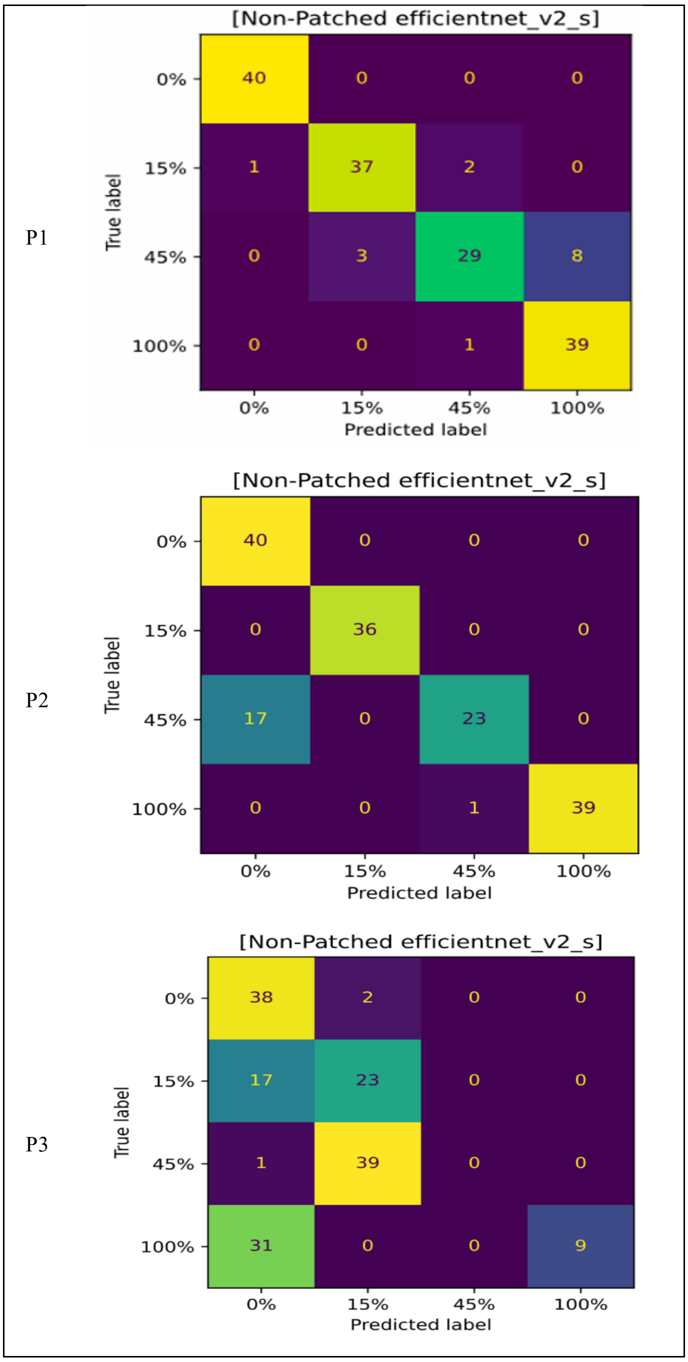

Fig. 4. Confusion matrix of EffecientNet classifiers in detection of tea adulteration; P1:Tea waste, P2:Foreign Tea, P3:Expired tea

The graphs related to error-train-validation and accuracy-train-validation of the Swin Transform classifier are presented in Fig. 5. In tea waste detection (P1), the model error graph fluctuates and does not reach full stability, and the accuracy increases slowly. This behavior indicates that the model faces challenges in convergence and probably requires more precise tuning of hyper-parameters. In foreign tea detection (P2), the model shows excellent performance. The validation error decreases rapidly and reaches convergence, indicating successful and stable learning. For expired tea (P3), the model performance is much better than the other two cases, and the sharp error reduction indicates its high ability to detect this type of fraud.

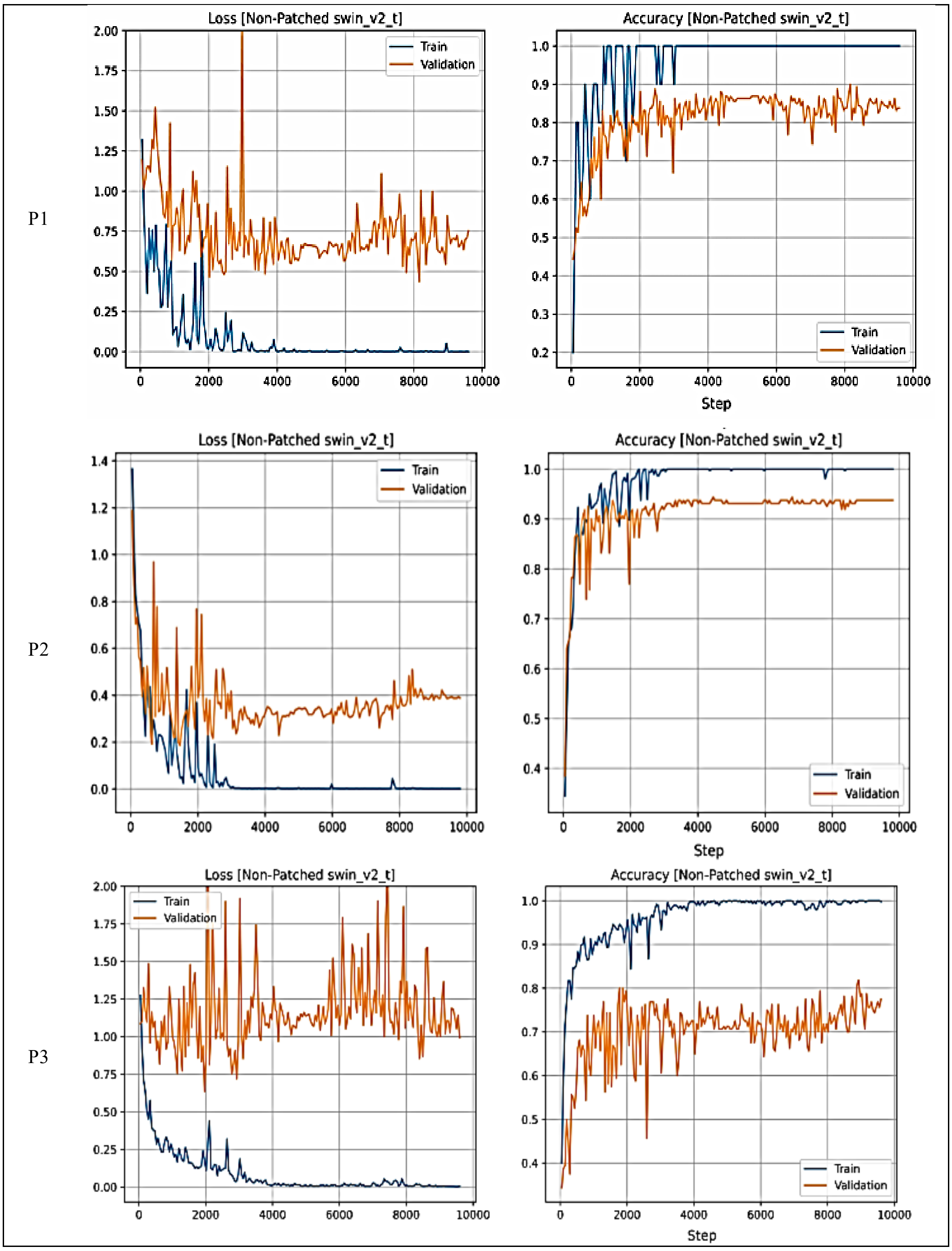

Fig. 5. Loss-train-validation and accuracy-train-validation of Swin Transform classifiers in detection of tea adulteration; P1:Tea waste, P2:Foreign Tea, P3: Expired tea

The confusion matrices of the Swin Transform classifier are shown in Fig. 6. It can be observed that the model demonstrated excellent performance in identifying tea waste, showing high accuracy in classifying the classes. In the case of tea grounds (P1), despite the convergence challenges, the confusion matrix shows high accuracy in the final classification. In the detection of foreign tea (P2), higher prediction errors are observed, which may be due to the complexity of the data or the need for further model tuning. The model performance for expired tea (P3) is better than P2, but still does not reach the high accuracy of P1.

The success of the Swin Transformer model in detecting foreign tea (P2) and expired tea (P3) is due to its Attention Mechanism-based architecture. Transformers are able to understand global relationships between different parts of an image. This capability allows the model to better detect a “foreign object” that disrupts the overall structure of the image (P2) or subtle and extensive color changes that are characteristic of stale tea (P3).

The averages of other evaluation metrics for the classifiers, including accuracy, precision, recall, and F1-score, are presented in Fig. 8. In the case of tea waste (P1), EfficientNetV2S not only scored higher in all metrics, but also had a more stable training process. This result seems reasonable considering the ability of CNNs to analyze texture. In the case of foreign tea (P2), SwinV2T performs better. The superiority of this model in the evaluation metrics, together with the fast convergence in the training process, indicates that the transformer architecture is more suitable for detecting structural anomalies in the image. In the case of expired tea (P3), the choice between the two models is more complicated in this case and depends on the final goal: if accuracy is the highest priority, EfficientNetV2S is the better choice. However, if the F1 score is more important, SwinV2T will be the superior option. The F1 score is the average of precision and recall, and a higher value indicates a better balance between type I errors (False Positives) and type II errors (False Negatives). In quality control applications where the cost of losing a false negative is high, the F1 score is a more appropriate metric than accuracy alone.

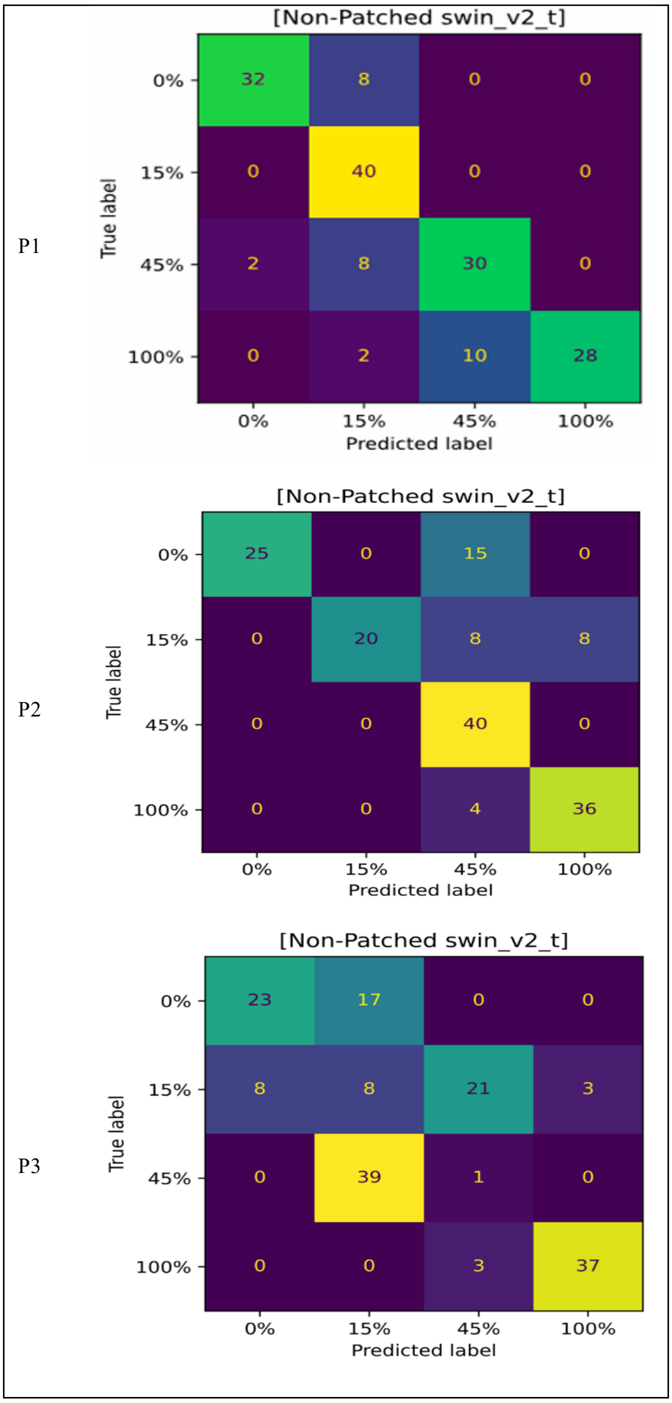

Fig. 6. Confusion matrix of Swin Transform classifiers in detection of tea adulteration; P1 :Tea waste, P2:Foreign Tea, P3:Expired tea

Fig. 7. Comparison of proposed classifiers from view point of performance criteria in detection of tea adulteration

3.3. Comparison of present paper with literature

This research can be compared to previous research in several ways:

a. Commonalities and points of confirmation

Confirmation of the effectiveness of deep learning in quality control: This research, in line with a large body of previous research, confirms the effectiveness of using machine vision and deep learning for automated, fast, and objective inspection of food products [31-32]. Numerous studies have shown that these methods can replace human inspection, which is often time-consuming, expensive, and dependent on subjective judgment.

Successful use of CNN for local feature analysis: The superior performance of the EfficientNetV2S model (a convolutional neural network or CNN) in detecting “tea waste” is consistent with the findings of many studies.

b. Direct comparison of CNN and transformer architectures in the tea domain

One of the most notable innovations of this research is the direct and performance comparison of two representatives of the most modern machine vision architectures (EfficientNetV2S and SwinV2T) on a single dataset and for a specific industrial application (tea adulteration detection). While much previous research has focused on one type of architecture (usually CNN), this research directly reveals the strengths and weaknesses of both approaches.

4. Conclusion

This study demonstrated that using deep learning algorithms can provide an effective and accurate solution for detecting tea fraud. The EfficientNet model performed better in identifying tea waste, while the Swin Transformer model showed greater capability in identifying foreign and expired tea. However, both models require improved parameter tuning in certain cases to enhance accuracy and reduce errors. Utilizing these technologies can help reduce fraud in the tea industry and boost consumer trust.

The performance of the models in identifying the expired tea was low due to its high similarity to the original tea, which is quite logical because the appearance similarity is not a good feature for distinguishing between them and it seems that artificial smell could be more effective.

The success of the EfficientNet (CNN-based) model in detecting “tea waste” is likely due to its superior ability to extract textural features and local patterns that are more prominent in tea waste. In contrast, the better performance of the Swin Transformer in detecting “foreign tea” and “expired tea” may be related to the architecture’s ability to understand global relationships and subtle color and shape differences in the entire image.

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