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Embedded system design for real-time detection of tobacco blue mold disease

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Abstract: The tobacco plant is grown in several regions globally as well as Turkey due to its significant adaptability. The occurrence of blue mold disease on tobacco leaves adversely affects the growth and development of the plant, leading to yield and economic losses. The traditional diagnosis of blue mold disease (*Peronospora tabacina* Adam) in tobacco leaves is time-consuming, which may delay control measures and accelerate the spread of the disease. This situation complicates early and accurate intervention strategies. Therefore, a real-time embedded system model was designed to detect diseased areas on tobacco leaves. Camera images were transferred to the embedded system, and symptomatic regions were identified using morphological operations implemented through Python software. In addition, convolutional neural network (CNN) models were employed to classify tobacco leaves as healthy or diseased. The performance of these models was evaluated on a dataset consisting of 1 600 healthy and 1 600 diseased tobacco leaf images taken in the Bafra district, Samsun, Turkey. As a result of the classification process, the system achieved a success rate of >93% across three different models. The developed real-time embedded system is expected to contribute to preserving productivity and sustainability in agriculture by enabling accurate and rapid detection of blue mold disease in tobacco leaves.

Keywords: Classification, disease detection, *Nicotiana tabacum* L., tobacco blue mold disease

Tütün mavi küf hastalığının gerçek zamanlı tespiti için gömülü sistem tasarımı

Öz: Tütün bitkisi adaptasyon yeteneğinin yüksek olmasından dolayı dünyanın ve Türkiye'nin pek çok bölgesinde yetiştirilmektedir. Tütün yapraklarında meydana gelen mavi küf hastalığı tütün bitkisinin büyüme ve gelişimini olumsuz etkilemektedir. Bu durum verim kaybına ve ekonomik kayıplara neden olmaktadır. Tütün yapraklarındaki mavi küf hastalığının (*Peronospora tabacina* Adam) geleneksel yöntemlerle teşhisi oldukça zaman alıcı olup kontrol süresinin uzamasına ve hastalığın hızla yayılmasına sebep olabilmektedir. Bu durum erken ve doğru müdahale stratejilerini zorlaştırmaktadır. Bu nedenle tütün yapraklarında meydana gelen hastalıklı alanların tespiti amacıyla gerçek zamanlı çalışan gömülü bir sistem modeli tasarlanmıştır. Kamera görüntüleri gömülü sisteme aktarılarak python yazılımı ile morfolojik işlemler uygulanarak simptomatik bölgeler tespit edilmiştir. Ayrıca tütün yapraklarını hastalıklı ve sağlıklı olarak sınıflandırmak amacıyla evrişimsel sinir ağları modelleri kullanılmıştır. Samsun/Bafra ilçesinde fotoğrafı çekilen 1 600 sağlıklı ve 1 600 hastalıklı tütün yaprağı içeren bir veri seti üzerinde bu modellerin performansı değerlendirilmiştir. Sistem, sınıflandırma işleminin sonucunda üç modelde %93 ve üzeri başarı oranı ile çalışmıştır. Geliştirilen gerçek zamanlı gömülü sistem tasarımı, tütün yapraklarındaki mavi küf hastalığının doğru ve hızlı bir şekilde tespit edilmesini sağlayarak, tarımda verimliliği ve sürdürebilirliği korumaya katkı sunacağı düşünülmektedir.

Anahtar kelimeler: Sınıflandırma, hastalık tespiti, *Nicotiana tabacum* L., tütün mavi küf hastalığı

1. Introduction

Approximately 5.8 million tons of tobacco are produced worldwide on about 3.2 million hectares of land (FAO, 2025). Tobacco is cultivated on 100 000 decares in Turkey, resulting in a production of 99 000 tons (TADAB, 2025). Around 50 000 farmers are engaged in contract-based tobacco cultivation in the country. It constitutes a significant source of employment considering the families of these farmers.

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Tobacco holds strategic importance for global and national economies; therefore, it is crucial to implement optimal cultivation practices free from diseases and pests to ensure its sustainable production. Diseases affecting tobacco leaves impair leaf integrity, resulting in decreased production and quality. The decrease in yield and quality reduces the income per unit area.

Blue mold disease (*Peronospora tabacina* D.B. Adam) infects developing tobacco plants when conidiospores and mycelial fragments are carried by spring winds and favorable conditions occur. The optimal temperature for the disease is between 18-24°C, and no development is observed below 2°C or above 27°C. The incubation period of the disease lasts between 4 to 11 days depending on various factors. The fungus continues to spread by producing new conidiospores at the end of each incubation cycle (Gıda Tarım ve Hayvancılık Bakanlığı, 2008). This disease is generally observed on the lower leaves, but sometimes can also infect the stem. The disease initially appears as light green areas on the upper surface of the leaf, followed by yellowish, nearly circular necrotic lesions. When viewed from the underside, the leaves are covered with a grayish or dirty white to pale lilac-colored mold layer. Lesions that rapidly expand on the leaf or stem become necrotic, dry out, and develop holes. The integrity of diseased leaves is compromised, and the stem may entirely rot and wither (Samsun İl Tarım ve Orman Müdürlüğü, n.d.)

The disease known as blue mould (or tobacco mildew) is typified by the appearance of macules on the leaves of the plant, which subsequently transition to a yellowish hue, and then a brownish one. Eventually, the affected areas dry out and deform the leaves. Early detection of foliar diseases is of critical importance for plant health and productivity. Early diagnosis significantly limits the spread and severity of diseases, increasing leaf yield and preserving leaf quality (Tobacco Experts Association, 2017).

The detection of plant leaf diseases is essential for maintaining plant health and preventing the spread of infection. The traditional method of visual inspection is effective in identifying disease symptoms on leaves. However, this approach can be time-consuming and difficult. Therefore, artificial intelligence-supported technologies play a crucial role in detecting leaf diseases (Türkoğlu, 2019).

Artificial intelligence, defined as the ability to computerize human mental functions, is frequently used in agriculture (Erkutlu et al., 2023). It makes significant contributions to sustainable agriculture by improving the efficiency of inputs such as irrigation, fertilization, and spraying, and is applied in monitoring greenhouses, controlling weeds, and tracking plant and soil conditions. These successful applications are vital for the sustainability of agriculture (Çakmakçı and Çakmakçı, 2023). The use of such technologies enhances production quality and agricultural efficiency.

Herein, an embedded system-based automatic control system was developed to detect potential defects that may occur on glass surfaces during production. The study utilized 90 images classified into three categories: intact, dented, and scratched. The system includes a camera, a conveyor belt system, and open-source software that operates with morphological image processing techniques and uses the Gaussian method for edge detection. The success rate was 93.2% using Support Vector Machine, Quadratic Discriminant Analysis, and Medium Tree classifiers. The system successfully detected defects with high accuracy, demonstrating the effectiveness of embedded systems in quality control (Bükücü, 2021).

Fan et al. (2018) proposed a novel algorithm for detecting tobacco plants from field images captured by unmanned aerial vehicles (UAVs) using deep learning methods. Initially, the acquired images undergo morphological processing. Subsequently, a convolutional neural network (CNN) is constructed and trained for classification using a dataset comprising images containing tobacco plants and those without. Finally, a post-processing step is applied to remove non-tobacco plants. As a result of this algorithm, good performance was achieved in tobacco detection, with average accuracy and error rates of 0.9370, 0.9126, and 3.94%, respectively (Fan et al., 2018).

Shao et al. (2017) developed a multi-feature automatic identification system that utilizes a genetic algorithm to optimize a backpropagation (BP) neural network, aiming to enhance the accuracy of tobacco leaf disease recognition. Using this system, the detection accuracy for diseases such as wildfire, weather fleck, and brown spot in tobacco leaves was 92.5%. The system exhibited high performance in accurately identifying these diseases, which are caused by bacterial, environmental, and fungal factors, respectively (Shao et al., 2017).

Xu et al. (2022) developed a new disease recognition method based on the Oriented FAST and rotated BRIEF (ORB) algorithm to improve the low efficiency in diagnosing tobacco leaf diseases. The FAST14-24 algorithm enhanced the edge detection rate of images, which was a weak point in the ORB algorithm. During the development of this method, 28 parameters were extracted through morphological features, color features, texture, and disease spots. The FAST14-24 algorithm achieved a recognition accuracy of 92% for early-stage frogeye and brown spot diseases, and 96% for mid-to-late stages (Xu et al., 2022).

Laily (2013) applied an artificial neural network using the Perceptron (single-layer learning) algorithm to detect diseases in clove and tobacco leaves. Eight types of tobacco leaf diseases, including reddish-brown spots, motling, and necrotic spots were analyzed. Diseased and healthy leaves were first collected and then classified. Diseases observed on the leaves were represented by bipolar values and used as training and testing data for the neural network. The method achieved a success rate of 66%, using 20 leaves for training and 10 for testing (Laily, 2013).

Avila-George et al. (2018) developed an Android-based software to detect damage caused by blue mold disease on tobacco leaves. A pattern recognition technique known as an artificial neural network was used to analyze tobacco leaf images. A total of 40 images were used for training and testing, achieving a success rate of 97.2%. Preprocessing, feature extraction, and classification steps were applied to implement the ANN model (Avila-George et al., 2018).

Swasono et al. (2019) developed a VGG16-based CNN model to automatically classify the susceptibility of tobacco leaves to harmful attacks. Utilizing the transfer learning technique, the model was trained on a dataset of 1 500 images and tested using 20% cross-validation. As a result of experimenting with various optimization techniques and parameter scenarios, the model was shown to classify the data with high accuracy (Swasono et al., 2019).

Although the detection of blue mold disease is generally carried out through field observations by farmers, not every farmer is able to accurately recognize the disease or assess its severity. Therefore, the developed algorithm enables the accurate and rapid identification of blue mold disease on tobacco leaves. Furthermore it allows for the effective planning of both the timing and method of intervention by determining the severity of the disease in the field; thereby, facilitating more informed and effective decision-making in disease management.

The aim of this study was to detect blue mold disease on tobacco leaves using artificial intelligence. First, the diseased areas on the leaves were identified through morphological image processing methods. A real-time embedded system was designed for the detection of these diseases. Finally, deep learning methods were employed to classify healthy and diseased leaves. This infrastructure aims to identify diseases in various tobacco types and to develop a general algorithm.

2. Materials and Methods

A sample model design that detects blue mold disease on tobacco leaves in real time is shown in Figure 1. This model is mounted on four legs, with LED lamps placed at each corner to provide illumination. Proper lighting is crucial for the accurate detection of diseased areas on the leaves. It has been observed that the accuracy rate of the model tends to decrease in areas with insufficient lighting. The system utilizes four LED lamps (1), a Kaan-brand webcam (2), a Raspberry Pi 3 Model B+(3), an HDMI-VGA converter (4), a monitor (5), a keyboard (6), and a mouse (7).

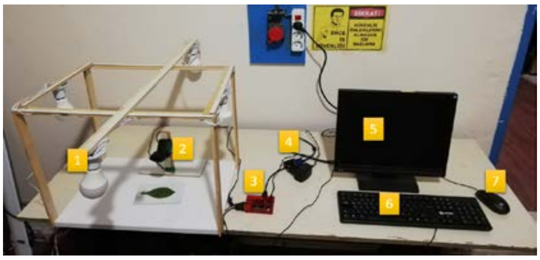

Figure 1. Real-time tobacco leaf disease detection model (In order: lamp, camera, raspberry pi 3, hdmı to vga converter, monitor, keyboard, mouse)

A USB camera was mounted on the model surface, with adjustable height and position according to the size of the tobacco leaves and the position of the light. The images captured by this camera were transferred to the Raspberry Pi 3 board. Afterwards, these images were processed using image processing techniques. This processing stage includes specially designed algorithms to detect and highlight diseased areas. As a result of the image processing, the diseased regions were visually displayed in real time on a screen connected to the Raspberry Pi 3 board. These regions were marked with the letter "h" and enclosed in a blue circle, as shown in Figure 2.

2.1. Real-Time disease detection

The detection of blue mold disease on tobacco leaves was carried out using a model designed with a Raspberry Pi for real-time detection. The images captured by the camera were resized to 200×200 pixels. After applying a threshold, the diseased areas within the determined contour values were marked with a blue circle and labeled with the letter "h" in real-time on the screen. Figure 2 shows the on-screen display of the diseased areas on tobacco leaves.

Figure 2. Diseased areas marked with a blue circle.

The images captured by the camera are processed on the Raspberry Pi 3 board and then transmitted via HDMI connection to a monitor and via the VNC program to a laptop on the same network for viewing (Figure 3).

Figure 3. Operation of the model performing real-time tobacco leaf disease detection

Calculations were made to detect diseased areas on leaves. These include the number of diseased areas (THS), the area covered by diseased regions on the total surface, and the total number of pixels in the image. This allows the proportion of diseased areas on the overall surface to be determined. These measurements are used to evaluate the number of diseased regions, the overall error rate, and the general quality of the product. In the equation below, THA is calculated.

THS: Total number of diseased areas, THA: Total area covered by diseased regions on the surface, TP: Total number of pixels

$$THA = THS/TP \quad (1)$$

Diseased areas on tobacco leaves were segmented from the background using image processing techniques, and the number of pixels in these regions was calculated. Regions with pixel values between 0 and 10000 were considered as diseased areas. These areas are marked with red/blue circles and labeled with the letter "h". The processing steps are presented in Figure 4.

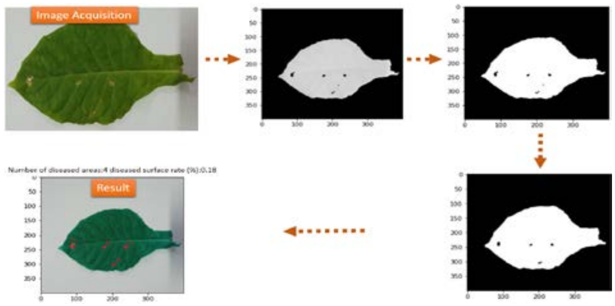

Figure 4. Stages of tobacco disease detection.

The number of diseases detected by the model and the information about the affected area are saved in a designated folder. These saved images are marked with a red circle and labeled with the letter "h". This allows the collected data to be analyzed and evaluated in detail at a later stage. Figure 5 shows the diseased areas on the tobacco leaves.

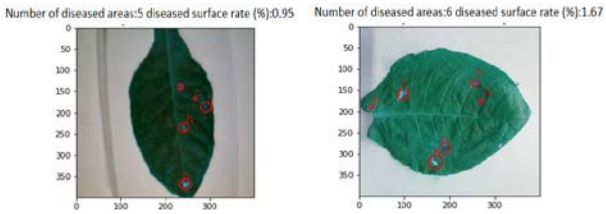

Figure 5. Number of diseased areas in tobacco leaves and their percentage.

2.2. Image processing

Picture processing fundamentally involves the transformation of a picture acquired by a camera from analog to digital format, subsequently generating a new image optimized for a specific goal. Digital images are obtained by sampling analog images. Images are represented in numerical formats and operate on a series of pixels. Each pixel can have a color value or grayscale tone, and an image is formed by the combination of these pixels. Image processing extracts and analyzes information from the image by performing mathematical operations on these pixels (Altunay, 2012). The steps of image processing consist of image acquisition, preprocessing, segmentation, feature extraction, interpretation, and recognition (Çayıroğlu, 2020).

In this study, shape-based methods, morphological features, and pre-trained CNN (Convolutional Neural Network) architectures were examined.

2.3. Morphological features

Morphological features are characteristics extracted from images using morphological image processing techniques. These features are used to define the structural properties of objects, such as their shape, size, structure, and topological characteristics (Kumar and Bhatia, 2014). Morphological features play a significant role in image analysis. Many applications, such as the classification, identification, and tracking of objects in images, require the use of these features.

2.4. Pre-trained CNN architecture

Several architectures based on CNN have been developed. In this study, pre-trained (transfer learning) models such as VGG-16, ResNet-50, and EfficientNetB6 were used. Transfer learning takes the feature extraction part of a pre-trained model and retrains the classification part for the target task. In other words, features learned in the source task are used in the target task, allowing for better results with less data (Hunter, 2018).

2.5. VGGNet

In their research paper titled "Very Deep Convolutional Networks for Large-Scale Image Recognition," K. Simonyan and A. Zisserman from the University of Oxford achieved significant success in the ImageNet competition using a dataset of 14 million images and 1 000 classes. Their model achieved an initial accuracy of 92% and ranked among the top five models (Kılıç, 2023).

2.6. ResNet

ResNet (Residual Network) is a significant architecture and method in the field of deep learning. Developed by Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun in 2015, ResNet achieved great success in the ImageNet classification competition (He et al., 2016). This architecture, based on micro-architectural modules, differs from traditional network architectures like VGGNet.

2.7. EfficientNet

EfficientNet is one of the scalable and high-performance artificial neural network architectures. Introduced in 2019 by Mingxing Tan and Quoc V. Le in their paper "Rethinking Model Scaling for Convolutional Neural Networks," this architecture stands out for achieving high accuracy in image processing tasks while efficiently utilizing computational resources (Tan and Le, 2019).

2.8. Performance metrics and classification process

In this study, binary classification was performed using three classification models. The performance of the models was evaluated in detail based on criteria such as accuracy and application flexibility.

Performance metrics

In this study, the CNN models VGG16, ResNet50, and EfficientNetB6 were analyzed in detail, and their classification performance was evaluated using various parameters. These parameters include the confusion matrix, F1 score, loss, accuracy, and recall values (Atacak, 2024). Figure 6 shows the confusion matrix for binary classification.

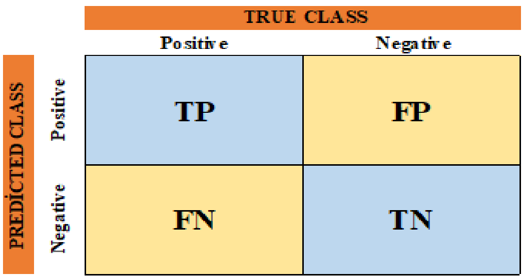

Figure 6. Confusion matrix for binary classification.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (2)$$

$$\text{Precision} = TP / (TP + FP) \quad (3)$$

$$\text{Recall (Sensitivity)} = TP / (TP + FN) \quad (4)$$

$$\text{F1 Score} = 2\times((\text{Precision} \times \text{Recall})/(\text{Precision} + \text{Recall})) \quad (5)$$

True positive (TP) refers to the number of cases where the model accurately predicts a positive situation, while true negative (TN) represents the number of cases where the model correctly identifies a negative situation. False positive (FP) refers to the number of cases where the model incorrectly predicts a positive situation, and false negative (FN) represents the number of cases where the model mistakenly identifies a negative situation.

Transfer learning training data

The CNN architectures VGG16, ResNet50, and EfficientNetB6 were employed, and their performances were evaluated to classify tobacco leaves affected by blue mold disease as "healthy" and "infected,". Tobacco leaves were collected from fields located in the Bafra district of Samsun, Turkey. Subsequently, photographs of both healthy and infected leaf samples were taken individually under controlled and well-illuminated conditions to construct the dataset. A total of 1 600 images of infected leaves and 1 600 images of healthy leaves were initially captured. This number was later increased through data augmentation techniques, resulting in a final dataset consisting of 5 200 healthy and 5 200 infected images. The training data are presented in Table 1, and sample images from the dataset are illustrated in Figures 7 and 8.

Table 1. Training data

	Total Number of Images: 3200		
	Images allocated for training %80	Images allocated for validation %20	Augmented training data %80
Pieces	2560	640	10240

Python programming language along with the OpenCV, Keras, and TensorFlow libraries were utilized while using the CNN architectures. The Jupyter IDE was used as the working environment. The study was conducted on a computer equipped with an Intel(R) Core(TM) i7-3630QM CPU @ 2.40GHz and an NVIDIA GeForce GT 650M.

Figure 7. Dataset of diseased tobacco leaves.

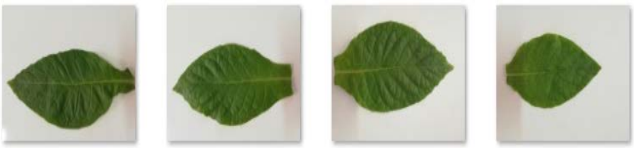

Figure 8. Dataset of healthy tobacco leaves.

3. Result and Discussion

Figure 9 and 10 present the accuracy and loss graphs, respectively. While all models show an increase in accuracy and a decrease in loss, the EfficientNetB6 model demonstrates the most successful performance with a steady rise in accuracy and a consistent reduction in loss, standing out in terms of generalization capability. Figure 11 displays the confusion matrix.

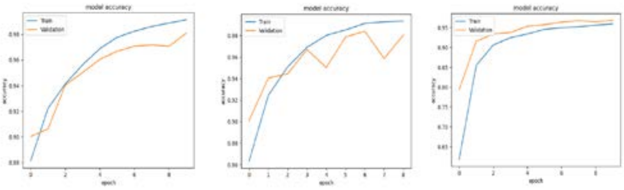

Figure 9. Accuracy progression of the models (in order: VGG16, Resnet50, EfficientNetB6)

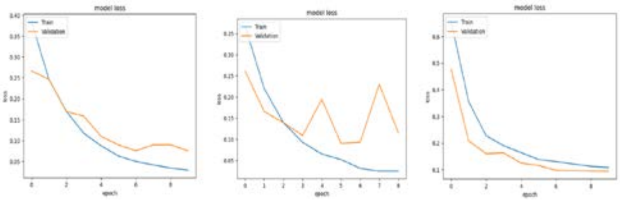

Figure 10. Loss progression of the models (in order: VGG16, ResNet50, EfficientNetB6)

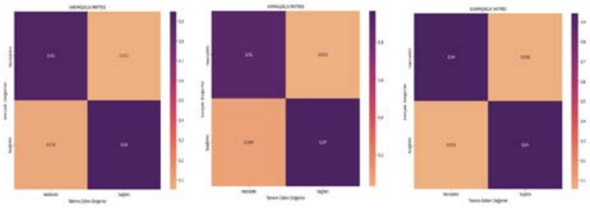

Figure 11. Confusion matrices for the models (VGG16, ResNet50, EfficientNetB6)

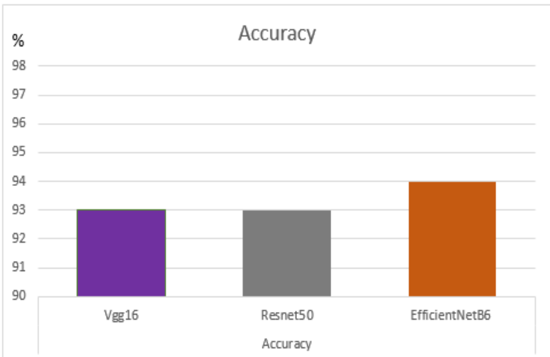

Figure 12. Accuracy rates of the CNN models.

Table 2. Evaluation data for CNN models.

	Accuracy	Precision	Loss	Recall	F1-score
VGG16	0.93	0,93	0.43	0.93	0.93
Resnet50	0.93	0,94	0.46	0.93	0.93
EfficientNetB6	0.94	0,94	0.16	0.94	0.94

EfficientNetB6 achieved the highest accuracy rate of 94% in distinguishing between "healthy" and "diseased" classes among the models used to classify blue mold disease on tobacco leaves. This indicates that the model generally made accurate predictions and effectively differentiated between healthy and diseased leaves. Although other models also exhibited high accuracy, their higher loss rates compared to EfficientNetB6 negatively affected their performance. A higher loss rate implies that the model's predictions deviate more from the actual values. Detailed performance data of the models are presented in Table 2 and Figure 12.

The study developed a model for real-time detection of diseased areas on tobacco plants. The model uses image processing techniques to identify the commonly occurring blue mold disease on tobacco leaves. The detected diseased areas are marked with a circle and labeled with the letter "h," making them visually distinguishable. Additionally, the percentage of the total area covered by diseased regions was calculated, and this information was recorded. As a result, the embedded system successfully detected diseased areas on tobacco leaves and classified them as either diseased or healthy. This classification achieved a success rate of 93.33%.

4. Conclusion

This study consisted of the development and evaluation of a model using image processing methods and deep learning algorithms to identify blue mold disease in tobacco leaves. The primary objectives was developing an effective image processing-based method to assess the health status of tobacco leaves, enabling early diagnosis of diseases, and contributing to the preservation of agricultural productivity.

The developed embedded system can detect diseased areas on tobacco plants in real time. It differentiates between healthy and diseased leaves by using image processing methods to identify and classify blue mold disease-affected areas quickly.

Three different convolutional neural network architectures (VGG16, ResNet, and EfficientNetB6) were examined in the study. The dataset obtained from tobacco leaves was expanded using data augmentation techniques and used to train these models. The EfficientNetB6 model achieved the highest accuracy (94%).

This study serves as a fundamental reference for the development of new systems and models aimed at disease detection in tobacco leaves. The findings can guide similar research and indicate the potential to lead future studies. Subsequent research may focus on the detection and classification of different types of disease observed in tobacco leaves. Additionally, diversifying deep learning methods and testing model performance with various datasets can provide significant contributions to expanding the scope of the current approach.

Conflict of interest

The authors declare no conflicts of interest.

Authorship contribution statement

C.E.: Data collection, laboratory work, article writing. Ç.C.B.: Planning, laboratory work, editing, article writing. A.K.: Planning, editing, article writing.

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