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Research article

Fungus Classification in Peanuts from Smart Lens Imagery Using Convolutional Neural Network

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Abstract

Classification of fungi in peanuts remains a critical challenge due to the microscopic nature of fungi, which requires specialized inspection methods. Without proper classification tools, there is a risk for consumers who consume contaminated peanuts, which can lead to severe health effects, particularly for those with fungal allergies. Traditional methods using microscopes or visual inspection by experts are impractical due to the bulky size of instruments, high cost, time-consuming process, and the potential for human error. This research addresses these limitations by proposing an efficient method for fungi classification in peanuts using convolutional neural network (CNN) and image processing techniques. The system utilizes a portable smart lens, an imaging device with high magnification (up to 50x), to capture detailed peanut images and paired with three CNN architectures: MobileNetv2, DenseNet121, and NASNetMobile. The experimental results demonstrated optimal performance with specific parameters for different peanut types. For ground peanuts, the system achieved 97.13% accuracy using 500x500 pixel grayscale images. Similarly, for peanut seeds, the system maintained 96.09% accuracy with 500x500 pixel RGB color images. This approach offers a practical, portable, and cost-effective solution for reliable fungal classification in peanuts.

Keywords: fungus classification; image processing; convolutional neural network; deep learning; smart lens

1. Introduction

Peanuts are field crops that are cultivated worldwide (Thitipechakul et al., 2015). In Thailand, peanuts are considered an essential economic crop because they can be grown yearly. Peanut seeds have high nutritional value and are a significant source of protein after meat. Therefore, they are in demand for consumption and processing. Peanuts are processed into animal feed and peanut oil, and into foods such as peanut butter, ground peanuts, snacks, etc. What we commonly see are ground peanuts that are seasoned with food flavors or peanut seeds that are roasted. Consumers may overlook the hidden danger

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behind the deliciousness, which is caused by the presence of peanut fungi. This is partly because fungi may be transparent or have thin filaments. Factors that affect fungal growth include humidity and temperature. Moreover, fungi in peanuts may be contaminated with aflatoxin, a toxin produced by fungi. Aflatoxin is a toxin that can withstand heat up to 268ºC (Jogloy, 2011). Therefore, standard heating cannot destroy this toxin. When the body is exposed to aflatoxin, it can cause seizures, breathing difficulties, liver damage, heart and brain swelling, etc.

Fungal contamination in food products, particularly in peanuts, poses significant health risks to consumers. Traditional fungal classification methods, including visual inspection and microscopic examination, present several limitations. Visual inspection can be error-prone, especially when dealing with transparent or filamentous fungi in their early growth stages. While microscopic examination offers more accurate results, it requires expensive equipment that may lack portability and is time-consuming to set up and use.

Recent advances in artificial intelligence (AI), particularly in deep learning (DL), have shown promising application in various domains, including agriculture and food safety (Russell & Norvig, 2020). Deep learning, a subset of machine learning (ML), employs artificial neural networks (ANNs) that mimic human brain function (Iorga & Neagoe, 2019). Among various DL architectures, convolutional neural networks (CNN) have demonstrated remarkable success in image processing and analysis tasks (Dhillon & Verma, 2020).

CNNs excel in processing visual data through multiple layers of artificial neurons, making them particularly suitable for tasks such as object detection and classification (Iorga & Neagoe, 2019). These networks have evolved into various architectures, including LeNet, AlexNet, VGGNet, and ResNet, each optimized for specific applications. The selection of an appropriate CNN architecture depends on factors such as task complexity, dataset characteristics, and available computational resources.

The detection of fungal contamination in food products has significant health implications (Cornely et al., 2019). Recent research has shown successful applications of CNN-based systems in fungal detection, achieving accuracy rates of up to 94.8% across different fungal types (Tahir et al., 2018). These systems typically employ sophisticated image processing techniques, including color transformation and image cropping, with standardized input dimensions of 128x128 pixels (Sardogan et al., 2018). Advanced computer vision techniques, implemented through platforms such as MATLAB and OpenCV, have further enhanced fungal detection capabilities. These approaches incorporate feature extraction methods like Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM) classification to differentiate between fungal spores and contaminants (Tahir et al., 2016; Nair et al., 2021). Notably, implementations using 16-layer CNN architecture have achieved classification accuracy rates of 98.03% (Prommakhot & Srinonchat, 2020). Transfer learning approaches utilizing pre-trained networks such as VGG16 and ResNet-50 have also shown promising results in fungal classification tasks (Habiba & Islam, 2021; Hangarge, 2023). Convolutional neural networks (CNNs) were used to classify 89 types of fungi, using images from microscopes with zoom up to 400 times. The dataset had 1,079 images, split into a 7:2:1 ratio for training, testing, and validation. The performances of various models in this experiment, including DenseNet, Inception ResNet, InceptionV3, Xception, ResNet50, VGG16, and VGG19, were compared. The results showed that DenseNet performed best, with a top 1 accuracy of 65.35% and a top 3 accuracy of 75.19%. Data augmentation improved performance by about 10% and the use of pre-trained weights from ImageNet helped increase accuracy by another 15%. A comparison between max pooling and average pooling found no significant difference, although average pooling required more training time (Rahman et al., 2023).

In classifying 5 genera of fungi, namely *Absidia, Aspergillus, Fusarium, Penicillium* and *Rhizopus*, and comparing the performance of VGG16, ResNet50 and InceptionV3, the researchers then improved the model's efficiency by combining all three models (Ensemble Learning) using probability averaging method, which provided high accuracy of up to 98.92% and was able to classify *Penicillium* and *Absidia* fungi correctly at 100%, while other fungi types were classified with accuracy exceeding 87% (Prommakhot & Srinonchat, 2024). Prommakhot and Srinonchat (2022) developed an enhanced 32-layer CNN using DropBlock optimization to classify five fungus species from microscopic images. The DropBlock technique outperformed traditional methods by blocking contiguous regions rather than individual neurons, significantly improving over KNN (82.68%) and SVM (83.88%) by approximately 15%. This research provides a practical AI solution for rapid, automated fungus identification in agricultural and medical applications, contributing to cost-effective disease diagnosis through enhanced microscopy analysis.

The existing research problem in the fungal detection system in peanuts is challenging because fungi are microscopic and require expensive, large microscopes for detection. Early-stage detection needs expert examination. Without microscopes, consumers may consume contaminated beans before detection, severely impacting health, especially for those allergic to fungi. Traditional laboratory microscopes (compound, phase-contrast, fluorescence) require controlled environments, trained operators, and significant infrastructure, making them impractical for routine field testing. Therefore, developing a detection system using affordable small cameras would benefit practical applications.

This research presents the development of an AI-powered fungal classification system for peanuts, leveraging deep learning techniques, specifically CNN architecture. The system aims to overcome the limitations of traditional classification methods by offering faster processing times, reduced dependency on expert analysis, and cost-effective implementation. While the system may not match the absolute accuracy of expert analysis, it provides a practical and efficient solution for routine fungal classification in peanut processing.

This research provides several important contributions to overcome the challenges of fungal classification in peanuts. Firstly, we develop a new classification system that uses a smart lens and an affordable camera in combination with Convolutional Neural Networks (CNNs). This system allows peanut producers to check for fungal contamination without needing expensive microscopes, making it practical for daily use. Secondly, we compare three CNN architectures, MobileNetV2, DenseNet121, and NASNetMobile, to find the best model for detecting fungi in peanut images. Our experiments show how these models work with different image types, such as RGB and grayscale, providing useful information for future research. Thirdly, this work helps improve food safety by offering a fast and reliable way to detect aflatoxin-producing fungi in peanuts. This can protect consumers from health risks and reduce losses for peanut businesses. These contributions support the use of Artificial Intelligence in agriculture, particularly for ensuring the quality of peanut products in places where resources are limited.

2. Materials and Methods

The research framework for detecting fungus in ground and peanut seeds is carried out according to the process shown in Figure 1.

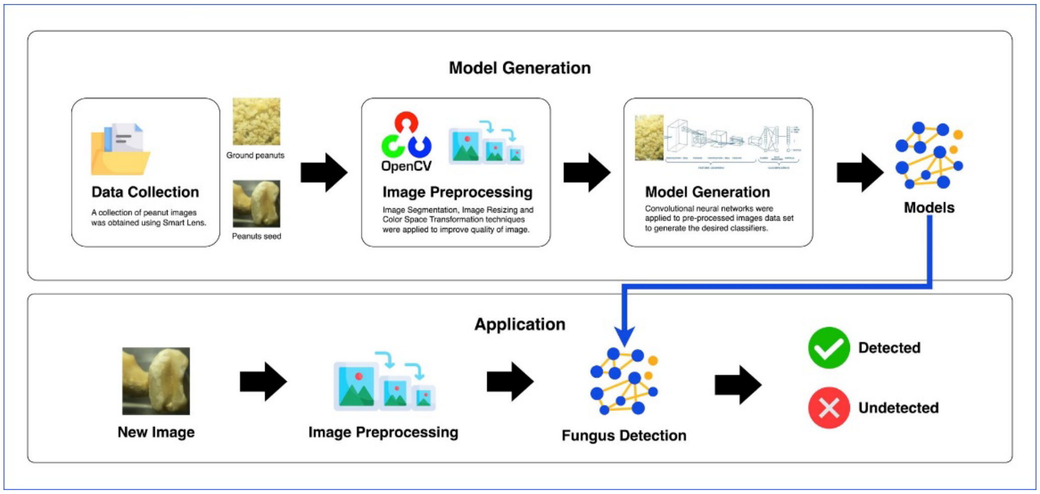
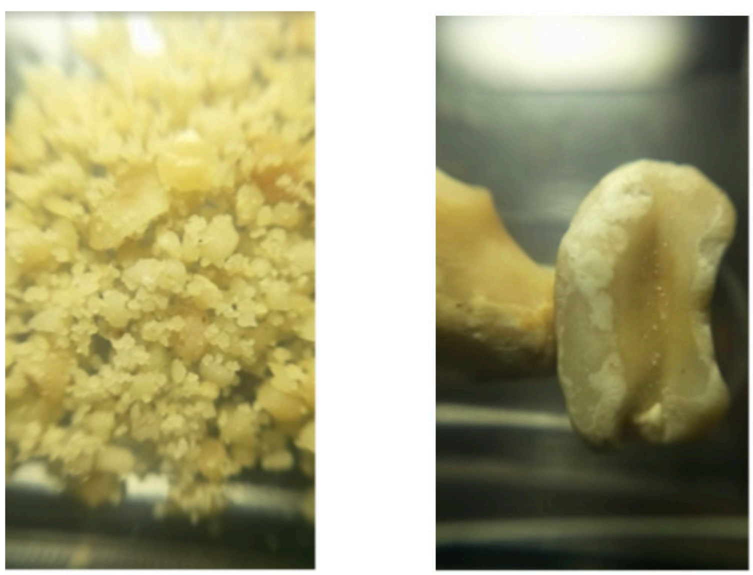


Figure 1. A conceptual research framework for detecting fungi in peanuts

From Figure 1, the research process in this study consists of 3 steps: (i) Data collection, (ii) Image preprocessing, and (iii) Model generation. Finally, the model is applied in the fungus classification application. Each step is summarized as follows:

As fungi in peanuts can occur both in ground peanuts and in whole peanuts, this study collected data from both ground and entire peanuts using a smart lens (the details are discussed in Section 2.1. Examples of the captured images are shown in Figure 2.



(a) Ground Peanuts (b) Peanut seed

Figure 2. Example of peanuts (a) Ground peanuts, (b) Peanut seed

After image collection, each image undergoes processing using OpenCV techniques to enhance image quality and facilitate subsequent steps, including classifier creation. Once the desired model is obtained, it is used in the application. For example, when an image is input into the system, the system examines it using the model. If fungus is found in the beans, the system reports "Detected"; if not found, it reports "Undetected".

2.1 Data pre-processing

Data preprocessing is essential in any machine learning or data analysis project. It involves cleaning, transforming, and organizing the data for analysis. This study divided data preprocessing into two subsections: data collection and data preparation.

2.1.1 Data collection

This section outlines the data acquisition process for the research, which targets the classification of fungal infections in ground and seed peanuts. Due to the small size of early-stage fungi, visual observation is challenging; therefore, specialized equipment—a smart lens—was employed for image capture and the data collection process.

1) Smart lens

A smart lens (Chulalongkorn University, 2020), as shown in Figure 3, is an accessory lens that can be used with a smartphone to magnify various objects. It has a magnification range from 20 to 50 times. The smart lens has a clip-on design and was used to collect images of fungal infections in peanuts. The innovative lens is a small and affordable camera. This is in contrast to traditional laboratory microscopes, which are not only expensive but also difficult to transport. This makes smart lenses practical for peanut producers who need a fast and cheap way to check their products.

Figure 3. Smart Lens

2) Image collection process

This study acquired image data using a Huawei Y9s smartphone camera coupled with a smart lens featuring magnifications of 20x, 40x, and 50x. Peanut images were gathered from diverse sources, including markets, shops, noodle stalls, and home roasting, during June-July 2020. Humidity was elevated within an enclosed experimental box using water to induce fungal growth. The box encompassed various peanut types alongside a water-filled glass and was hermetically sealed to exclude light. The data consists of a total of 960 images, which were divided into two categories: (i) 480 images of ground peanuts and (ii) 480 images of peanut seeds. This information is summarized in Table 1.

Table 1. Data from the image collection process

Lens	Ground Peanuts		Peanut Seeds		Total
	Train	Test	Train	Test	
20x	126	34	128	32	320
40x	128	32	128	32	320
50x	128	32	128	32	320
Total	**382**	**98**	**384**	**96**	**960**

2.1.2 Data preparation

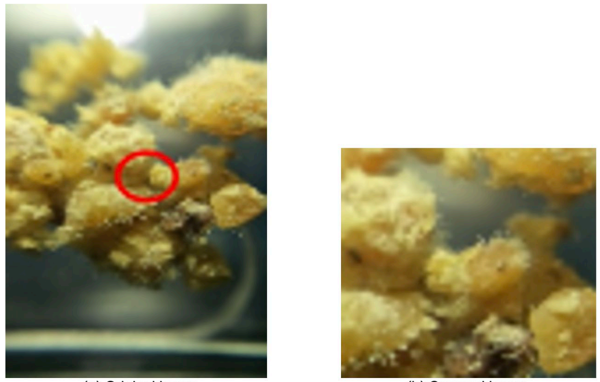
After the data were collected using a smart lens, the images had to undergo image processing before they could be used to create a classifier. This involved preparing the images in a suitable format for classifier creation using various image preparation processes. These processes include (1) image cropping, (2) image resizing, and (3) color space transformation and are explained as follows.

1) Image cropping

Image cropping partitions an image into regions or sub-images of interest. In this research, images from a Huawei Y9s mobile phone camera (6000x8000 pixels) were segmented to select the central area containing the beans. The image cropping comprised the following steps: (i) importing the original image data, (ii) determining the image center in the form (X, Y), and (iii) cropping the image using the values (X, Y) to a size of 1500x1500 pixels along both the X and Y axes, resulting in a square image of size 1500x1500 pixels. This process is illustrated in Figure 4(a), which displays the original image, while Figure 4(b) exhibits the cropped image of the region of interest with a size of 1500x1500 pixels.

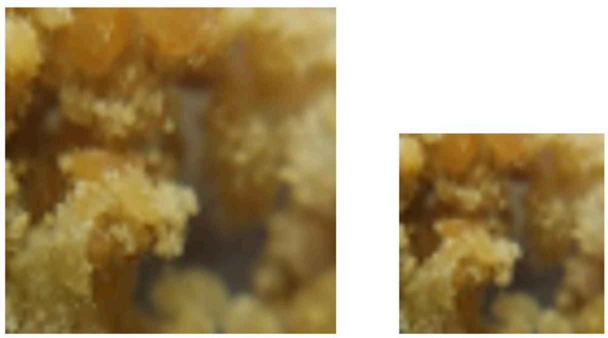
2) Image resizing

Segmenting the region of interest results in large images, which requires increased processing time when creating a classifier. To reduce the learning time needed to build the classifier, this research resized the images into various sizes to determine the most suitable size (Figure 5). The image resizing involved the following steps: (i) the input data was the segmented image of the region of interest (size 1500 x 1500 pixels), (ii) the user-specified width and height of the desired image size were received, (iii) the image was resized to the user-specified width and height, and (iv) the resized image was saved to the specified location.



(a) Original image (b) Cropped image

Figure 4. An example of image cropping of the region of interest



(a) Original image (b) Resized image (300x300)

Figure 5. An example of image resizing: (a) the original image with 1500x1500 pixels, (b) the image after being resized to 300x300 pixels.

The image sizes tested as inputs for the model were: (i) 50x50 pixels, (ii) 100x100 pixels, (iii) 150x150 pixels, (iv) 200x200 pixels, (v) 250x250 pixels, (vi) 300x300 pixels, (vii) 350x350 pixels, (viii) 400x400 pixels, (ix) 450x450 pixels, and (x) 500x500 pixels.

3) Color space transformation

The conversion of color space aims to transform the image from the standard RGB (Red Green-Blue) color space to test if fungi can be more clearly visible in other color spaces. The color spaces of interest in this research are (i) RGB (original color), (ii) L*a*b*, (iii) HSV, (iv) YCbCr, and (v) Grayscale.

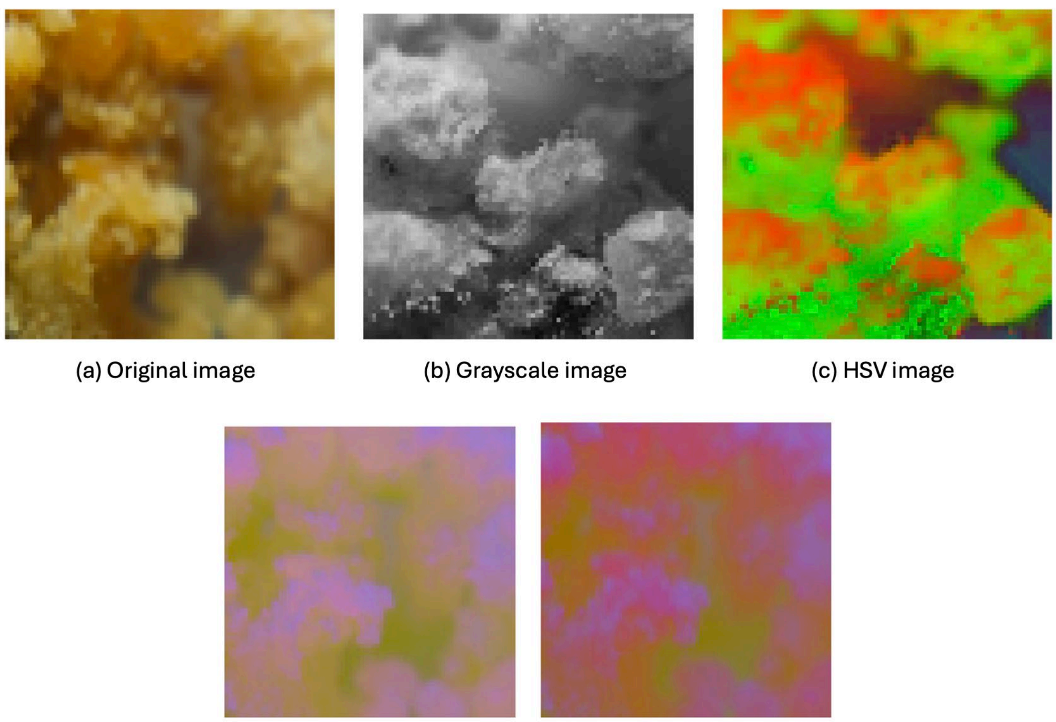
The CIE L*a*b* or CIELAB color system considers 3 components: the L* axis represents lightness with values ranging from 0-100, where 0 is black, and 100 is white. The a* axis describes the color axis from green (-a*) to red (+a*). The b* axis represents the color axis from blue (-b*) to yellow (+b*).

HSV separates brightness from the color of the image pixel. The HSV color space is represented by a three-dimensional vector consisting of H for hue, S for saturation, and V for intensity of the color (Kullimrat, 2012).

YCbCr is one of the color signal systems used in digital video component systems (the other being RGB). The difference between YCbCr and RGB is that YCbCr displays images using a luminance signal and two-color difference signals, while RGB displays images using red, green, and blue signals. In YCbCr, the letter Y represents luminance, Cb represents blue minus luminance (B-Y), and Cr represents red minus luminance (R-Y) (Kumeechai, 2018).

In grayscale mode, images are represented using only shades of gray, varying from black to white. There are 256 levels of gray intensity (Gonzalez & Woods, 2018), with 0 representing black and 255 representing white.

The color space transformation is carried out according to the following 4 steps: (i) the input data is the image data that was cropped and resized, (ii) the mode was received from the user, (iii) the color mode was converted to the specified color space, and (iv) the resized image was saved in the designated area. Examples of color mode conversion are shown in Figure 6: Figure 6(a), the original image is in RGB, Figure 6(b), the image in grayscale color space, Figure 6(c), the image in HSV color space, Figure 6(d), the image in L*a*b* color space and Figure 6(e), the image in YCbCr color space.



(a) Original image (b) Grayscale image (c) HSV image

(d) L*a*b* image (e) YCbCr image

Figure 6. Examples of images in different color spaces

2.2 Methods

An imaginative or convolutional neural network (CNN) is an artificial neural network that simulates human vision by processing and combining spatial sub-regions. A CNN has three main layers: (i) Convolution layer, the first layer, transforms the image by extracting essential features such as sharpness, color, in pixel form. The extraction process is called filter or kernel. The filter is applied to the first pixel of the input data and then slides over all image pixels. The output is called the feature map; (ii) the pooling layer, the intermediate layer between the convolution layer and full connection layer, reduces the feature map size (Yan et al., 2018) but still retains the ability to recognize the object. There are two methods: max pooling, which calculates the maximum value of the filter when applied to the image according to the pixel, and the new result is the maximum filter value in each stride set; and average pooling, which calculates the average value; and (iii) the fully connection layer, the final layer, aggregates various features between feature map and output by applying deep learning to the flattening result to create a model.

The neural network architecture encompasses a diverse range of options. In this research, we selected a total of three CNN architectures to create classifiers for fungus classification in peanuts from smart lens imagery: (i) MobileNetV2, (ii) DenseNet121, and (iii) NASNetMobile. All three models are compact in size, such as MobileNetV2 with only about 3.5 million parameters. However, these models are still highly accurate and efficient for image classification tasks and were more suitable for this research than large models because the dataset used for model training was quite limited. Using small models reduces the risk of overfitting, which often occurs when using larger models on smaller datasets. These models are not only considered as efficient but also as real-world applicable. Small models can be used more conveniently on smartphones, allowing applications to run faster and more efficiently for fungal classification.

2.2.1 MobileNetv2 architecture

MobileNetV2 is an improved artificial neural network architecture over MobileNetV1, developed by Google (Howard et al., 2017, Sandler et al., 2018). This version enhances the performance of MobileNetV1 to suit the use with mobile devices, such as smartphones. MobileNetV2 has a size of 16 MB, which allows for fast processing and supports various classification tasks, such as classification and object detection. The initial convolution layer of MobileNetV2 has 32 filters, and there are 19 convolution layers. The input image data is reduced to 224x224 x3 pixels within the architecture, which defines the width and height of the image used in this architecture. The components of the MobileNetV2 architecture are shown in Figure 7. MobileNetV2 has been applied in works such as in in Kaur et al. (2023).

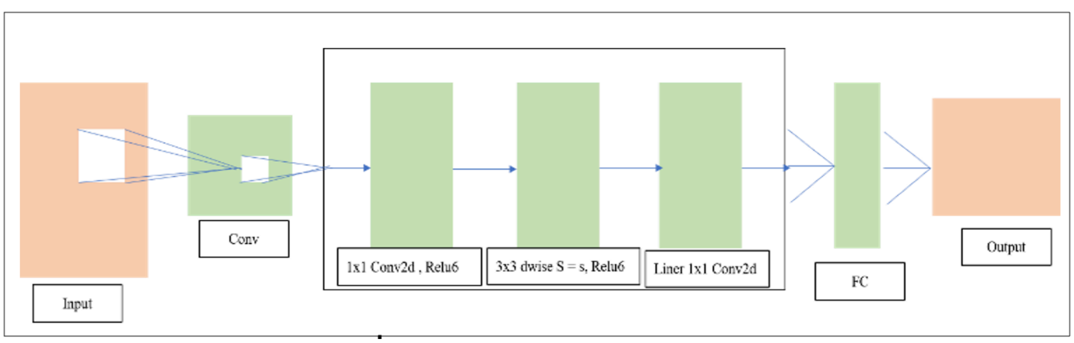


Figure 7. MobileNetv2 architecture

2.2.2 DenseNet121 architecture

DenseNet121 is a convolutional neural network architecture developed in 2017 for object detection using images (Huang et al., 2017). It is similar to ResNet in that it uses residual connections but differs in that DenseNet connects the output of every layer to the next layer. This allows for more efficient information flow and feature reuse, leading to better performance.

DenseNet121 has a size of 33 MB and has been improved to make it easier to access data and directly access the color levels of image data. This makes it more efficient for object detection tasks, as it can process images more quickly and accurately. DenseNet121 has 121 convolution layers, with an initial convolution layer with 64 filters. The components of the DenseNet121 architecture are shown in Figure 8. DenseNet121 has been applied in works such as in Aral et al. (2018), Yang et al. (2018) and Sooksatra et al. (2019).

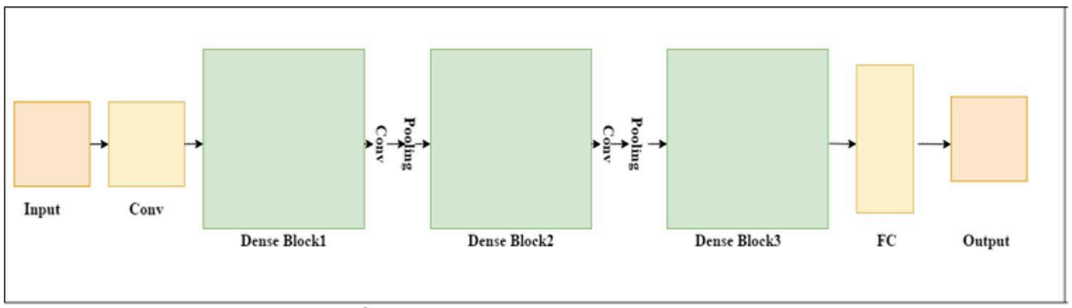


Figure 8. DenseNet121 architecture

2.2.3 NASNetMobile architecture

NASNetMobile is a flexible and scalable deep-learning approach for image classification developed by Google Brain (Adedoja et al., 2019). At 23 MB, it is compact and suitable for mobile devices. The architecture consists of a series of convolutional cells that are repeated multiple times. Before being fed into the network, the input image data is resized to 224x224x3 pixels. The components of the NASNetMobile architecture are illustrated in Figure 9. NASNetMobile has been utilized in studies such as in Nobrega et al. (2018), Saxen et al. (2019), and Zhang and Davison (2020).

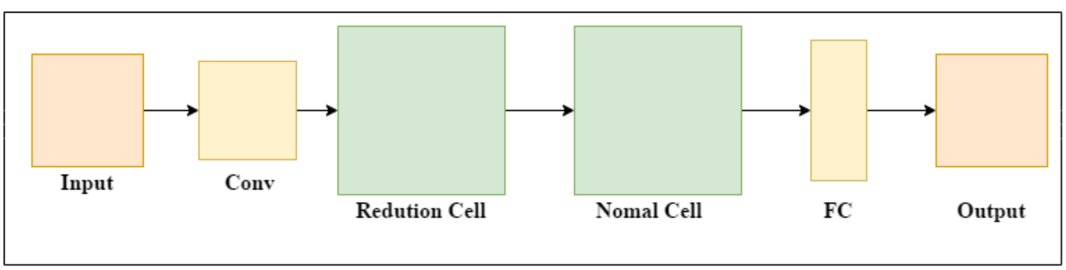


Figure 9. NASNetMobile architecture

3. Results and Discussion

This research was aimed at developing a fungi classification system for peanuts using affordable smart lenses. To determine the highest accuracy for practical fungal classification applications, we compared three compact and fast CNN architectures: MobileNet2, DenseNet121, and NasNetMobile. Therefore, after preprocessing the image data, we applied a deep learning approach with a convolutional neural network (CNN) to create the classifier. Three experiments were conducted on ground peanuts and peanut seeds to evaluate the classification performance: Set 1: the classifier based on image size; Set 2: the classifier based on color space; and Set 3: the classifier based on CNN architecture. The results and discussion are as follows.

3.1 Ground peanuts

3.1.1 The classifier based on image size

The original peanut images were large and time-consuming to process for classifier creation. The images were resized to different smaller sizes to determine the optimal dimensions. The experiments used different image sizes: (i) 50x50 pixels, (ii) 100x100 pixels, (iii) 150x150 pixels, (iv) 200x200 pixels, (v) 250x250 pixels, (vi) 300x300 pixels, (vii) 350x350 pixels, (viii) 400x400 pixels, (ix) 450x450 pixels and (x) 500x500 pixels. This experiment used grayscale color space and MobileNetV2 (based on the results from Table 3 and Table 4). The images were processed for 100 epochs (with grayscale color space with MobileNetv2). To prevent overfitting from using 100 epochs, we used early stopping, which stops training when the validation set accuracy does not improve, and dropout to reduce over-memorizing the training data. The result is presented in Table 2.

Additionally, Table 2 indicates that the optimal image size for ground peanuts was 500x500 pixels, which gave the highest classifier creation accuracy. The accuracy was 97.17%, and the loss was 0.0914.

3.1.2 The classifier based on color spaces

Since fungi in peanuts may appear more clearly in different color spaces, we changed the image color space to enhance the visibility. We used five different color space: (i) RGB, (ii) YCbCr, (iii) HSV, (iv) grayscale, and (v) L*a*b*. The results are shown in Table 3. The grayscale images provided the best performance and visibility for fungi classification among the five color channels. MobileNetV2 was the best classifier architecture, which achieved an accuracy of 0.9817. The worst performing color space was YCbCr, which had an accuracy of 0.9504.

3.1.3 The classifier based on CNN architecture

Three convolutional neural network architectures are compared for classifier creation: (i) MobileNetV2, (ii) DenseNet121, and (iii) NASNetMobile. Table 4 shows the results. MobileNetV2 architecture achieved the highest accuracy of 0.9817 for ground peanuts with grayscale images, compared to NASNetMobile and DenseNet121, which achieved accuracy of 0.9459 and 0.8775, respectively. Given the limited size of our dataset, a smaller model was more suitable and reduced the risk of overfitting. Moreover, grayscale images and cropping the peanut images enabled clear classification of the fungal patterns with the MobileNetV2 model.

Table 2. The accuracy and loss of the classifier based on image size of ground peanuts using MobileNetV2

Image Size	Train		Test	
	Accuracy	Loss	Accuracy	Loss
50x50	0.9321	0.1461	0.7755	0.1369
100x100	0.9661	0.0928	0.7551	0.6506
150x150	0.9687	0.0741	0.8673	0.5155
200x200	0.9504	0.1194	0.8265	1.1952
250x250	0.9817	0.0397	0.8673	0.6862
300x300	0.9634	0.0916	0.8163	1.0998
350x350	0.9504	0.1282	0.6122	1.5383
400x400	0.9321	0.1463	0.5816	0.2888
450x450	0.9843	0.0763	0.7653	0.2772
500x500	**0.9713**	**0.0914**	**0.8469**	**0.5628**

Table 3. The accuracy and loss of the classifier based on color spaces of ground peanuts using MobileNetV2

Color Space	Train		Test	
	Accuracy	Loss	Accuracy	Loss
RGB	0.9713	0.0914	0.8469	0.0186
YCbCr	0.9504	0.1555	0.7551	0.1285
HSV	0.9713	0.0841	0.8265	0.0090
Greyscale	**0.9817**	**0.0643**	**0.8571**	**0.0385**
L*a*b*	0.9530	0.1084	0.6224	2.0687

Table 4. The accuracy and loss of the classifier based on CNN architecture of ground peanuts

CNN Architecture	Train		Test	
	Accuracy	Loss	Accuracy	Loss
MobileNet2	0.9817	0.0643	0.8571	0.0385
DenseNet121	0.8775	0.3615	0.6385	2.2377
NasNetMobile	0.9459	0.2359	0.4217	0.6579

3.2 Peanut seeds

3.2.1 The classifier based on image size

Classifier creation was compared with different image sizes of peanut seeds to reduce the image size and find the optimal size. The following image sizes are experimented with (i) 50x50 pixels, (ii) 100x100 pixels, (iii) 150x150 pixels, (iv) 200x200 pixels, (v) 250x250 pixels, (vi) 300x300 pixels, (vii) 350x350 pixels, (viii) 400x400 pixels, (ix) 450x450 pixels, and (x) 500x500 pixels. The image color space was RGB, and MobileNetV2 was used as the CNN architecture in this experiment set (based on the results from Section 3.2.2 and 3.2.3, which were the most suitable color space and CNN architecture). The images were processed for 100 epochs, and Table 5 presents the details of the image size comparison.

From Table 5, the results in the test dataset show that the image size of 400x400 pixels was the most suitable for creating the classifier in peanut seed fungal classification, giving an accuracy value of 0.9167. The image size that gave the lowest accuracy value was 350x350 pixels, giving an accuracy value of 0.6875.

Table 5. The accuracy and loss of the classifier based on image size of peanut seeds

Image Size	Train		Test	
	Accuracy	Loss	Accuracy	Loss
50x50	0.9375	0.1492	0.9062	0.1369
100x100	0.9479	0.1796	0.8125	0.6506
150x150	0.9297	0.1756	0.8854	0.5155
200x200	0.9453	0.1593	0.7500	1.1952
250x250	0.9193	0.2332	0.8854	0.6862
300x300	0.9297	0.1761	0.7604	1.0998
350x350	0.9401	0.1617	0.6875	1.5383
400x400	**0.9036**	**0.2863**	**0.9167**	**0.2888**
450x450	0.9401	0.1464	0.8750	0.2772
500x500	0.9609	0.0989	0.8542	0.5628

3.2.2 The classifier based on color spaces

There were five color channels: (i) RGB image, (ii) YCbCr image, (iii) HSV image, (iv) Grayscale image, and (v) L*a*b* image. From Table 6, it can be concluded that among the five color channels, the RGB image provided the highest performance and visibility of the fungal infection, using the MobileNetV2 architecture to create the classifier, which gave an accuracy value of 0.9609. The color space that provided the lowest performance was the grayscale image, which gave an accuracy value of 0.9167.

Table 6. The accuracy and loss of the classifier based on color spaces of peanut seeds

Color Space	Train		Test	
	Accuracy	Loss	Accuracy	Loss
RGB	**0.9609**	**0.0989**	**0.8542**	**0.5628**
YCbCr	0.9557	0.1400	0.8750	0.3151
HSV	0.9453	0.1405	0.8646	0.3071
Grayscale	0.9167	0.2208	0.9167	0.1343
L*a*b*	0.9349	0.1578	0.8021	0.5128

3.2.3 The classifier based on CNN architecture

The classifier was created by evaluating three convolutional neural network architectures: MobileNetV2, DenseNet121, and NASNetMobile. The results are shown in Table 7. It is evident that the MobileNetV2 architecture achieved the highest accuracy of 0.9609, using the RGB image set of peanut seeds as the input.

Table 7. The accuracy and loss of the classifier based on CNN architecture of peanut seeds

CNN Architecture	Train		Test	
	Accuracy	**Loss**	**Accuracy**	**Loss**
MobileNet2	0.9609	0.0989	0.8542	0.5628
DenseNet121	0.9010	0.2837	0.3187	2.1528
NasNetMobile	0.9323	0.2423	0.4563	7.4681

The research demonstrated a cost-effective fungal classification system for peanuts using smart lenses and CNN architectures, with MobileNetV2 achieving the highest performance (98.17% training accuracy for ground peanuts and 96.09% for seeds). Significant gaps remain notable due to overfitting (evident from test accuracies around 85%), the absence of a validation set, missing real-time performance metrics, and a lack of direct comparisons with traditional microscopic methods. While the system provides advantages in portability and automation compared to expensive microscopes. However, the research contributes to advancing automated food safety inspection technologies by balancing accuracy with accessibility, which is particularly beneficial for regions where expensive microscopy equipment is impractical.

4. Conclusions

This research focused on the classification of fungal infections in peanuts by using a smartphone camera with portable smart lens that could zoom in on peanuts by up to 50x to capture detailed peanut images, and by using convolutional neural network (CNN) integrated with image processing techniques like cropping, resizing, and color conversion. Among the architectural choices, MobileNetV2 was adopted due to its commendable statistical performance because it balances high accuracy and fast processing. The findings can be summarized as follows: (i) Customized classifiers were constructed with varying image dimensions. Optimal results were attained with a resolution of 500x500 pixels for fragmented peanuts, yielding an accuracy of 97.13%. Similarly, the ideal image size for peanut seeds was determined to be 500x500 pixels, achieving an accuracy of 96.09%. (ii) Diverse image color space was explored to create classifiers. Notably, the HSV color space yielded the most accurate classification for ground peanuts at 97.13%, while the RGB color space exhibited superior performance for peanut seeds, yielding an accuracy of 94.53%. There may not be all kinds of fungi present in our dataset, so results might differ in the real world, but the smart lens-based system proved small and inexpensive, making it easy for peanut makers to check their products for aflatoxin risks. This system, although limited in some respects, can save money for peanut businesses and keep food safe for consumers. In future work, more comparative analysis with other systems should be performed and adapted to run on mobile phones for ease and convenience.

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6. Authors' Contributions

Kwankamon Dittakan conceived and designed the research methodology, designed and set up the experiments, participated in discussions, wrote the conclusion, and contributed to writing the manuscript. Jirawat Thaenthong conducted the literature review, participated in discussions, wrote the conclusion, and contributed to manuscript preparation. Sulakkana Rodkue conducted the literature review, collected data, and conducted experiments. Phutphisit Thungklang conducted the literature review, conducted experiments, participated in discussions, and contributed to writing the manuscript.

7. Conflicts of Interest

The authors declare that they have no conflicts of interest

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