COMPARING DIFFERENT OF DEEP LEARNING MODELS FOR CLASSIFICATION MUSHROOM MORPHOLOGY

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วชรพล เกตวงษา. 2565. **การเปรียบเทียบรูปแบบการเรียนรู้เชิงลึกที่แตกต่างกันสำหรับจำแนกประเภทสัณฐานวิทยาของเห็ด**. วิทยานิพนธ์ปริญญาวิทยาศาสตรมหาบัณฑิต สาขาวิชาวิทยาการคอมพิวเตอร์ บัณฑิตวิทยาลัย มหาวิทยาลัยขอนแก่น.

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บทคัดย่อ

การศึกษาครั้งนี้เนื่องจากในประเทศไทยมีผู้เสียชีวิตจากการรับประทานเห็ดมีพิษต่อเนื่องทุกปี เป็นเรื่องยากที่จะแยกแยะระหว่างเห็ดมีพิษและเห็ดที่กินได้ เนื่องจากเห็ดมีพิษและเห็ดที่กินได้บางชนิดมีลักษณะทางสัณฐานวิทยาที่คล้ายคลึงกัน ในงานวิจัยนี้ ผู้เขียนสนใจที่จะศึกษาเกี่ยวกับโครงข่ายประสาทเทียมเพื่อเปรียบเทียบสถาปัตยกรรมสามแบบ ได้แก่ AlexNet, ResNet-50, GoogLeNet กับสถาปัตยกรรมที่เสนอ เพื่อใช้ในการจำแนกเห็ดมีพิษและกินได้ทั้งหมดห้าชนิด แบ่งเป็นเห็ดมีพิษสองชนิดได้แก่ *Inocybe rimosa* และ *Amanita phalloides* และเห็ดกินได้สามชนิดได้แก่ *Amanita princeps*, *Russula delica* และ *Phaeogyroporus portentosus* โดยใช้วิธี Convolutional neural network (CNN) และ Region convolutional neural network (R-CNN) ผลการทดลอง CNN และ R-CNN พบว่าสถาปัตยกรรมที่มีความแม่นยำที่สุดสำหรับการจำแนกเห็ดโดยใช้วิธี CNN คือสถาปัตยกรรม ResNet-50 และ GoogLeNet มีความแม่นยำที่ 99.50% และวิธี R-CNN คือสถาปัตยกรรม AlexNet, ResNet-50 และสถาปัตยกรรมที่เสนอมีความแม่นยำที่ 98.00% และสถาปัตยกรรมที่เร็วที่สุดสำหรับการจำแนกประเภทเห็ดโดยใช้ CNN และ R-CNN คือสถาปัตยกรรมที่เสนอใช้เวลา 40 วินาทีและ 7.47 นาทีตามลำดับ สถาปัตยกรรมที่เสนอสามารถลดเวลาการฝึกอบรมและการทดสอบได้และยังคงรักษาระดับความแม่นยำในระดับสูง ในการจำแนกเห็ดโดยใช้ CNN และ R-CNN สถาปัตยกรรมที่เสนอมีความแม่นยำ 99.00% และ 98.00% ตามลำดับ

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ABSTRACT

The study was motivated by the number of deaths from eating poisonous mushrooms in Thailand every year. It is difficult to distinguish between poisonous and edible mushrooms because some poisonous and edible mushrooms have similar morphology. In this research the author is interested in studying on convolutional neural network in order to compare three different architectures: AlexNet, ResNet-50, GoogLeNet, with the proposed architectures, in the classify five species of poisonous and edible mushrooms, two species of poisonous: *Inocybe rimosa*, and *Amanita phalloides*, and three species of edible: *Amanita princeps*, *Russula delica*, and *Phaeogyroporus portentosus*, using the convolutional neural network (CNN) and region convolutional neural network (R-CNN). In the experiments using CNN and R-CNN, it was found that, the most accuracy architecture for mushroom classification using CNN were ResNet-50 and GoogLeNet architectures at 99.50%, and R-CNN were AlexNet, ResNet-50 and proposed architectures at 98.00%. And fastest architectures for mushroom classification using CNN and R-CNN was proposed architectures at 40 seconds and 7.47 minutes, respectively. The proposed architecture can reduce training and testing time while maintaining a high level of accuracy. In mushroom classification using CNN and R-CNN, the proposed architectures have accuracy of 99.00% and 98.00%, respectively.

Goodness Portion to the Present Thesis is Dedicated

for my Parents and Entire Teaching Staff

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CHAPTER I
INTRODUCTION

1.1 Introduction and background

Thailand is in the tropics zone above the equator, the climate of the north and northeast is tropical savanna climate with hot, humid, and dry climates and an average year-round temperature of more than 18 degrees, the natural vegetation of most of them is Tropical Rain Forest Dry, Evergreen Forest Hill, and Mixed Deciduous Forest. From mentioned above, making a vast array of flora and fauna. Kingdom of fungi comprises mold, mushrooms, and yeast, they are eukaryotic cells which do not include chlorophyll that makes it unable to make its own food for this reason they must consume food from other living beings. Mushrooms are also economically significant because farmers can earn money from collecting and selling wild mushrooms. Mushrooms can be found after two-three days of rain between May and September. Moreover, mushrooms are full of nutrients, a good source of protein, small amounts of calories and unsaturated fats, a rich source of vitamins and iron (Ria et al., 2021), and it contains antioxidants. Mushrooms can be found often in deciduous dipterocarp forests, mixed deciduous forests, and dry evergreen forests in the northern and northeastern parts of Thailand. There are more than two to three million species of mushrooms in the world, and these can be simply divided into two types: poisonous and edible mushrooms (Wibowo et al., 2018; Mešić et al., 2020; Chitayae, Sunyoto, 2020). Some poisonous mushrooms are very similar to edible mushrooms. There are old methods that can classify poisonous mushrooms regarding to folk wisdom is to heating mushrooms in the same pot with rice: a color change of the rice demonstrates that the mushrooms are poisonous, or boiling mushrooms and stirring with a silver spoon, if the spoon changing from silver to black, it also meaning poisonous mushrooms. However, for all above experiments cannot identify every type of poisonous mushrooms because some poisonous mushrooms are not affected by these tests. The basic morphology of poisonous mushrooms is brightly colored, there are scales on the mushroom caps, colorful scales on the cap and a circle under the cap, for example. If the harvester is inexperienced, it can be harmful by consuming a poisonous mushroom. Poisonous mushrooms affect the nervous system and lead to death if consumed exceedingly (Zahan et al., 2021). A large number of people die from consuming poisonous mushrooms every year.

Deep learning is part of machine learning (ML), it is a set of instructions built for machine learning, it has automated learning by mimicking the operation of the human brain. Deep learning is an Artificial neural network (ANN) with multiple layers of nodes and parallel processing allows for complex processing, with high speed and high accuracy. Additionally, deep learning methods are more accurate than human classification because they were trained by large datasets, the accuracy of the model depends on the amount of training data used, which is high amount of training data leads to high accuracy. Presently, deep learning is used in various fields, such as facial recognition (Khan et al., 2019; Lin M et al., 2020), plant disease detection (Rahman et al., 2019; Militante et al., 2019), and autonomous vehicles, for object classification (Alhabshee, bin Shamsudin, 2020; Tarmizi, Aziz, 2018). Deep learning consists of three components: the input layer, the hidden layer, and the output layer.

As the problems mentioned above, the author therefore proposed a new architecture as an improvement on the AlexNet architecture and addition of inception module from the GoogleNet architecture, because AlexNet architecture is easy to understand, it's not complicated and has processing speed. And GoogLeNet architecture has an inception module structure which is parallel processing that can multi-level feature extraction at the same time. By comparing training time and classification accuracy of poisonous and edible mushrooms from three pre-trained architectures: AlexNet, ResNet-50, and GoogLeNet with the proposed architecture for the classification of five species of poisonous and edible mushrooms: *Inocybe rimosa*, *Amanita phalloides*, *Amanita princeps*, *Russula delica*, and *Phaeogyroporus portentosus*.

1.2 Objective of the research

1.2.1 Proposes a new architecture used for the classification of poisonous and edible mushrooms using CNN and R-CNN methods.

1.2.2 To compare the accuracy of each architectures in deep learning for classification poisonous and edible mushroom morphology.

1.3 Scope and limitation of the study

1.3.1 Scope of the research

1.3.1.1 Using CNN to classify the morphology of poisonous and edible mushrooms.

1.3.1.2 Using R-CNN to detect the location of poisonous and edible mushrooms.

1.3.1.3 Compare the classification accuracy of each models.

1.3.1.4 There are 5 types of mushrooms: 2 types of poisonous mushrooms and 3 types of edible mushrooms.

1.3.2 Limitation of the research

1.3.2.1 There is limited mushroom dataset for training and testing.

1.3.2.2 The number of mushroom dataset in each class is unbalanced.

1.3.2.3 The background image is not various.

1.4 Expected benefits

1.4.1 The proposed model is able to accurately classify poisonous and edible mushrooms.

1.4.2 The proposed model can shorten the training time.

1.4.3 Able to classify the morphology of poisonous and edible mushrooms.

CHAPTER II
LITERATURE REVIEWS

This chapter discusses a review of the literature and related research used in the research, including:

2.1 Literature related to neural network

2.2 Literature related to mushrooms

2.3 Literature related to efficacy assessment

2.4 Related research to classification

2.1 Literature related to neural network

2.1.1 Neural network

Neural network is a computer system that simulates the functions of the human brain neural network (Militante et al., 2019). It consists of three parts: the first part is input layer, the second part is the hidden layer, the middle layer is the layer that determines the performance of the model. This layer can contain more than one layer, depending on how it is designed, the more layers it takes the more computational time. And finally, the Output layer is the layer that shows the results of the hidden layer, neural networks structure is shown in Figure 1.

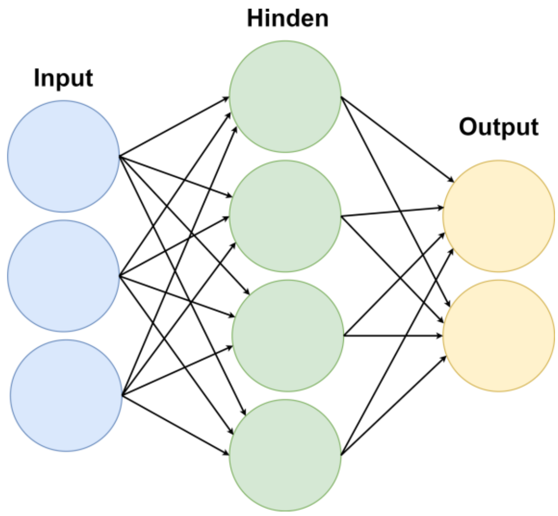

Figure 1 Neural networks structure.

2.1.2 Convolutional neural networks (CNN)

Convolutional neural networks are Artificial neural networks (ANNs) with multiple layers. It is a type of deep learning model for processing grid-formatted data such as images. It is a popular deep learning algorithm that is used for image analysis and object recognition (Dominguez-Catena et al., 2021). CNN is highly efficient for image processing because it will extract the features of the image out, as it is passed on to the next layer, the extracted features become more and more complex. The CNN contains convolutional layers, pooling layers, a rectified linear unit, fully connected layers, and a softmax layer (Lee et al., 2020; Sajanraj, Beena, 2018; Naranjo-Torres et al., 2020). The most common layers are Convolution, activation, and pooling in one structure may contain more than one of these layers to increase computational complexity, the more layers, the more processing time. Convolutional neural networks architecture is shown in Figure 2.

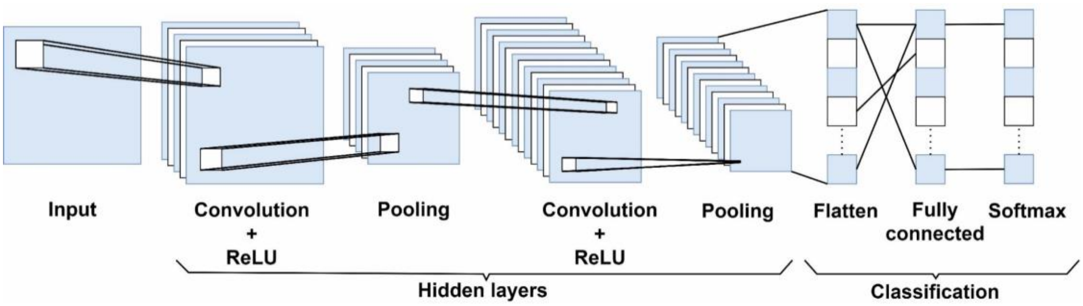

Figure 2 Convolutional neural networks architecture. (Ketwongsa et al., 2022)

The input layer is layer that determines the size and dimensions of the image, for example an image of 227x227x3 pixels is an RGB image of 227x227 pixels.

The convolution layer uses a filter to detect features in an image in order to find features such as borders, colors, shapes, etc (Dong, Zheng, 2019). The filter scrolls through each part of the image to examine its attributes, dimensions that commonly used is 3x3 5x5. An example using a 3 × 3 filter is shown in Figure 3.

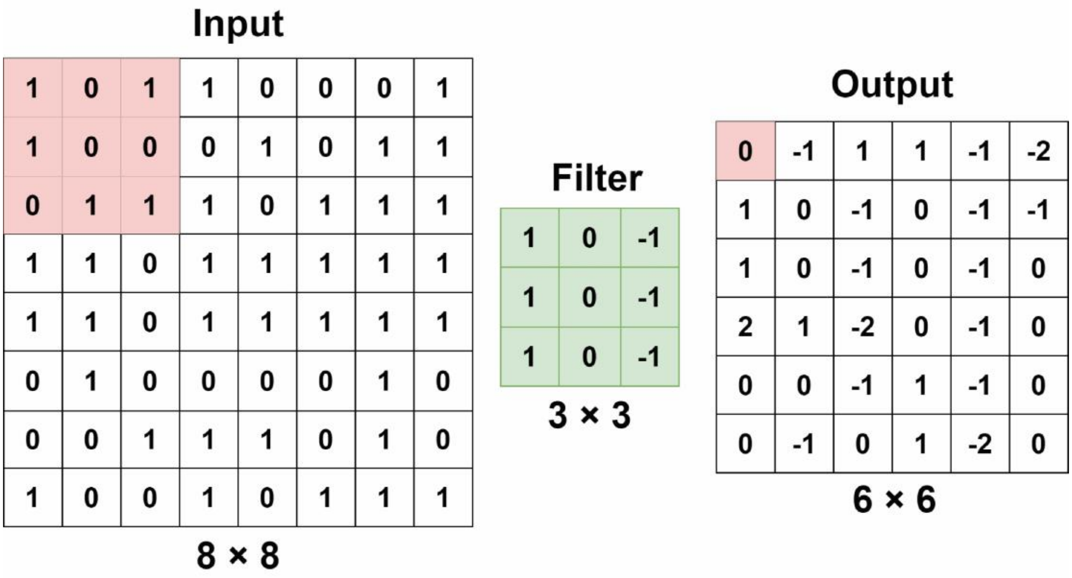

Figure 3 Convolution layers. (Ketwongsa et al., 2022)

The calculation method is to multiply the filter by the input and add the result, for example: (1×1) + (0×0) + (1×-1) + (1×1) + (0×0) + (0×-1) + (0×1) + (1×0) + (1×-1) = 0.

The activation function uses a Rectified Linear Unit (ReLU), meaning that if the input is greater than 0, the output is the same, and if the input is less than 0, the output is always set to 0 (Mostafa et al., 2022). ReLU is defined by the following equation:

$$f(x) = \max(0, x) \tag{1}$$

The pooling layer is a layer connected from convolutional layer to reduces the number of parameters, simplify, and reduces the training time (Dominguez-Catena et al., 2021; Arora et al., 2020; Guo et al., 2017). There are two types of pooling: max pooling and average pooling (Hsiao et al., 2018; Nirthika et al., 2021; Momeny et al., 2022). In Figure 4 is an example of max pooling, with a pooling size of 2 × 2.

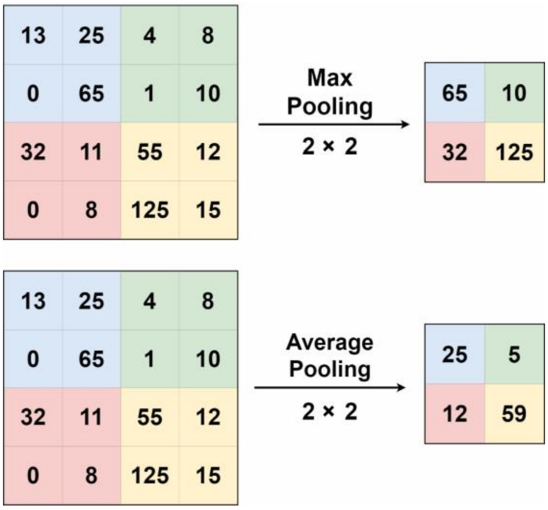

Figure 4 Pooling layers. (Ketwongsa et al., 2022)

The flattening layer is to make the vector multidimensional, become a one-dimensional vector, for the convenience of data analysis, is shown in Figure 5.

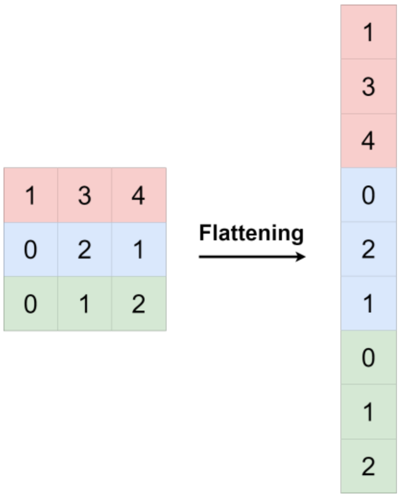

Figure 5 Flattening layers. (Ketwongsa et al., 2022)

The fully connected layer is a layer that connects the flattening layer and the softmax layer. By combining all features to classify the next layer (Dong, Zheng, 2019; Zheng, 2021).

The softmax layer is a layer that defines the probability of giving predictions for each class (Mostafa et al., 2022). For example, when an input dog image, softmax will give to how many percentages to be dog and cat.

2.1.3 Region convolutional neural networks (R-CNNs)

The R-CNN method was proposed to draw a bounded box around the object for detection because the CNN method is designed to classification objects. Object detection is an AI that detects objects in computer vision to detect objects in photos or videos, such as humans, animals, cars, buildings, and other objects. Examples of object detection methods are R-CNN, Fast-RCNN, Faster-RCNN, YOLO, SSD, etc. The workflow of R-CNN consists of 4 steps: the first step, a selective search for areas in the image that may contain interesting objects. The second step, training, and fine tuning on CNN models for each region proposal (Yanagisawa et al., 2018). The third step, bring the features obtained from second step into the SVM for classification. Finally step, bounding boxes are created around objects with the greatest precision. The R-CNN architecture is shown in Figure 6.

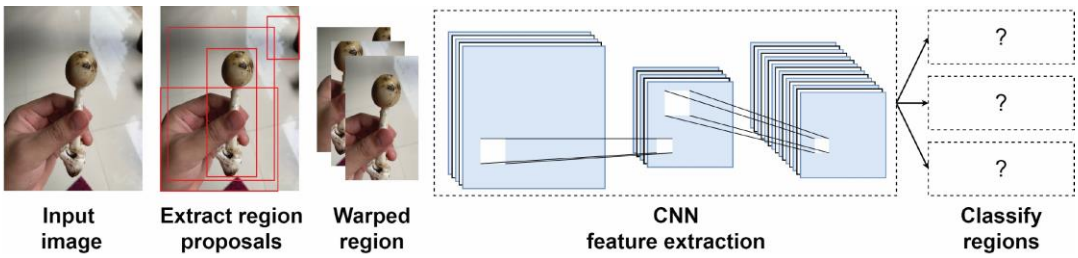

Figure 6 Region convolutional neural networks. (Ketwongsa et al., 2022)

2.1.4 AlexNet

AlexNet architecture is a CNN with eight layers, it was trained from the ImageNet which has more than one million images and over 1,000 categories database. The AlexNet architecture consists of five convolution layers, three max pooling layers, and three fully connected layers (Sun et al., 2021; Beeharry, Bassoo, 2020). It has an image input size of 227 × 227 × 3 pixels. Five convolution layers: the first layer consists of 96 filters, filter size 11 × 11 pixels. The second layer consists of 256 filters, filter size 5 × 5 pixels. The third layer consists of 384 filters, filter size of 3 × 3. The fourth layer consists of 384 filters, filter size of 3 × 3 pixels. The last layer consists of 256 filters, size of 3 × 3 pixels. Afterwards, each convolution completed, Rectified Linear Units (ReLu) and max pooling are always performed (Wan et al., 2018; Tariq et al., 2022). The AlexNet architecture is shown in Figure 7.

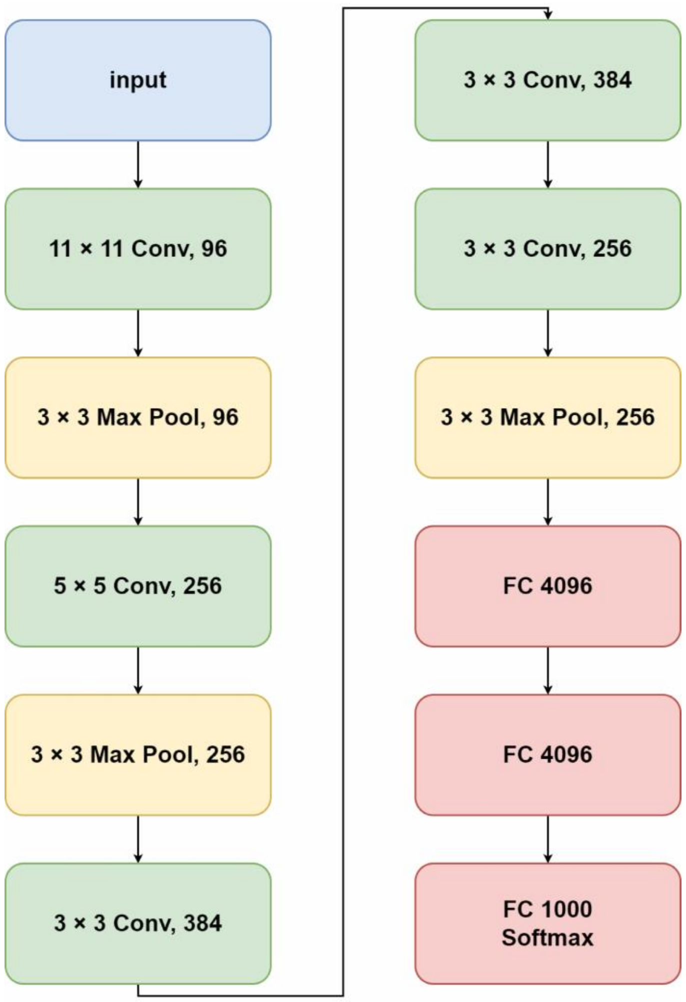

Figure 7 AlexNet architecture. (Ketwongsa et al., 2022)

2.1.5 ResNet-50

ResNet-50 architecture is a CNN that is fifty layers deep. ResNet-50 consists of input size of 224 × 224 × 3 pixels, sixteen bottleneck building blocks, forty-eight convolution layers, and one fully connected layer (Rahmathunneesa, Ahammed Muneer, 2019; Mukti, Biswas, 2019). Bottleneck building blocks have the same and different types as shown in Figure 9. Sixteen-layer bottleneck building blocks: block 1 to 3 consists of the first layer has 64 filters, filter size 1 × 1, the second layer has 64 filters, filter size 3 × 3, and the last layer has 256 filters, filter size of 1 × 1. Block 4 to 7 consists of the first layer has 128 filters, filter size 1 × 1, the second layer has 128 filters, filter size 3 × 3, and the last layer has 512 filters, filter size of 1 × 1. Block 8 to 13 consists of the first layer has 256 filters, filter size 1 × 1, the second layer has 256 filters, filter size 3 × 3, and the last layer has 1024 filters, filter size of 1 × 1. Block 14 to 16 consists of the first layer has 512 filters, filter size 1 × 1, the second layer has 512 filters, filter size 3 × 3, and the last layer has 2048 filters, filter size of 1 × 1 (Zhao X et al., 2022). There are several types of ResNet architectures, for example: ResNet-18, ResNet-50, and ResNet-101.

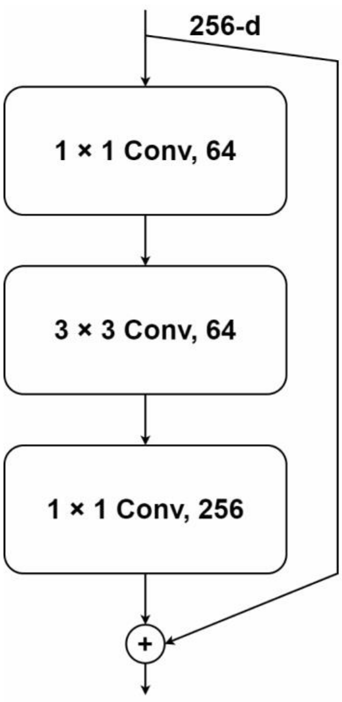

Figure 8 Bottleneck building block. (Ketwongsa et al., 2022)

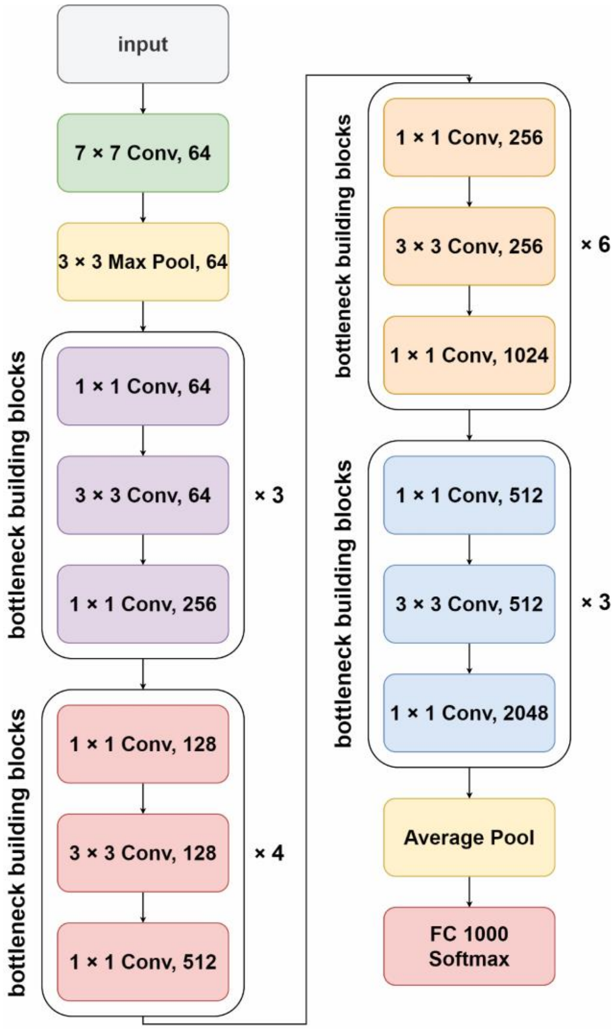

Figure 9 ResNet50 architecture. (Ketwongsa et al., 2022)

2.1.6 GoogLeNet

GoogLeNet architecture is a CNN that is twenty-two layers deep (Yuesheng et al., 2021). GoogLeNet was designed to incorporate the concept of an inception module (Balagourouchetty et al., 2020) and it has an image input size of 224 × 224 × 3 pixels. The inception module has parallel processing, it contains convolutions of 1x1, 2x2, 5x5 and Max Pooling 3x3 sizes (Jasitha et al., 2019; Haritha et al., 2020; Lin C et al., 2020). In Figure 10, GoogLeNet was designed with nine inception modules. When data are sent to an inception module, they are divided into four groups for parallel processing and merged into one set when leaving the module. The inception module is shown in Figure 11.

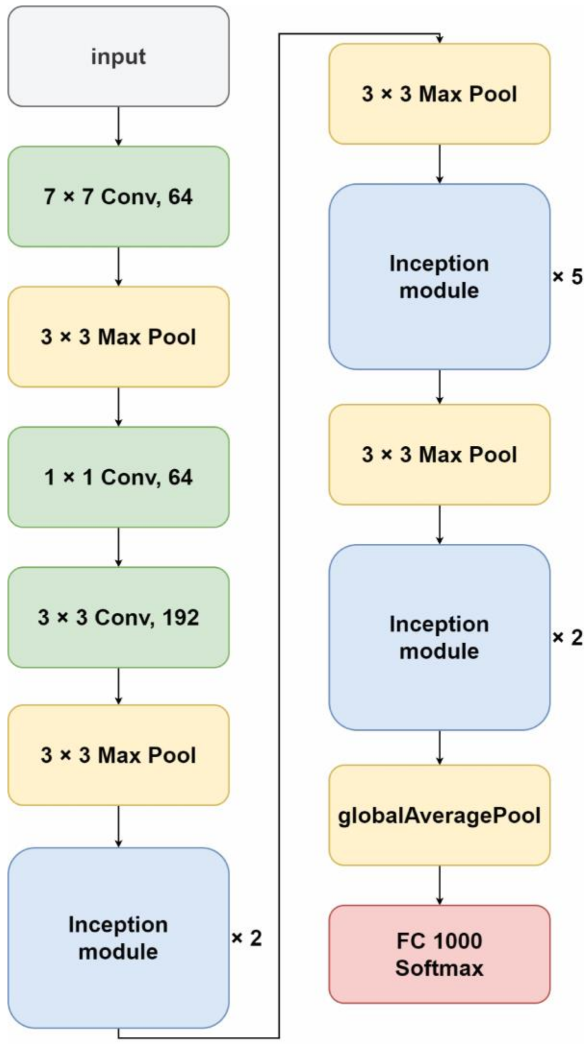

Figure 10 GoogLeNet architecture. (Ketwongsa et al., 2022)

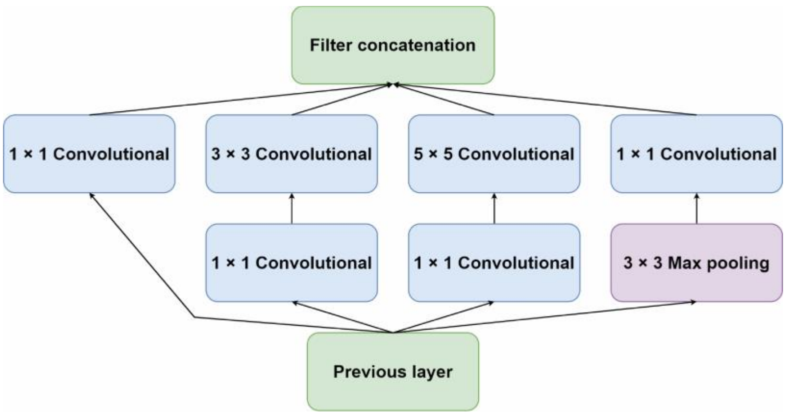

Figure 11 Inception Module. (Ketwongsa et al., 2022)

2.2 Literature related to mushrooms

2.2.1 Mushroom

There are between two and three million different species of mushrooms in the world. Mushrooms belong to the fungi kingdom, as low-level plants because they do not have chlorophyll, making them unable to photosynthesize, therefore needing nutrients from other organisms to grow. Mushrooms have long been used as a staple in cooking and can be used in many types of cooking because it is high protein, high in healthy fats, low in calories, many vitamins and iron. Currently, there are various types of mushrooms which can be divided into 2 types: poisonous and edible mushrooms. Some poisonous mushrooms if eaten, can cause allergic reactions, dizziness, vomiting or death.

2.2.2 Mushroom components

Cap or pilleus is the top part of the flower. mushroom has a different Cap shape, such as convex, conical, bell-shaped, smooth, rough, etc.

Gill or lamelta is the part under the cap, looks like a sheet or thin ribs arranged together.

Stalk or stipe is the part attached to the cap, there will be different lengths and colors. Some mushrooms do not have a stalk, such as *Auricularia auricula-judae*.

Ring or annulus is a thin membrane that holds the cap and stalk stalk together when the mushroom is young. And it will be absent when the mushrooms grow.

Volva outer veil is the part that covers the entire mushroom when it is young and breaks off like a blooming mushroom.

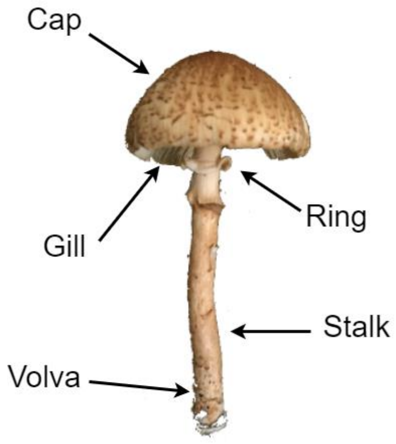

Figure 12 Mushroom components.

2.2.3 Poisonous mushroom

2.2.3.1 *Inocybe rimosa*

The morphological characteristics are the cap is yellowish brown, the cap is embossed, the skin is rough, the edge of the hat is torn when blooming, the stalk is white, has fine hairs. The main toxin is muscarine, after eating about 30 minutes to 2 hours it will affect the nervous system. Gastrointestinal tract irritation, diarrhea, profuse sweating, lacrimation, salivation (Naksuwankul et al., 2022). If a person has an allergic reaction, it can cause a bradycardia and lead to death. It is common in northern and northeastern of Thailand.

Figure 13 *Inocybe rimosa*.

2.2.3.2 *Amanita phalloides*

The morphological characteristics are pure white, when young they have a white shell that resembles an eggshell. The white cap will tear as it grows. The surface of the cap is smooth, in the shape of an inverted pan, the flesh is thick and the base is wide, similar to that of many edible mushrooms. Most of this type of mushroom will born a single flower, not grouped together. It is one of the most dangerous poisonous mushrooms. The main toxin is α-amanitin which directly affects the liver, kidneys, blood, cardiac and brain systems and is well absorbed in the gastrointestinal tract causing death of the eater (Naksuwankul et al., 2022). It is common in northern and northeastern of Thailand.

Figure 14 *Amanita phalloides*.

2.2.4 Edible mushroom

2.2.4.1 *Russula delica*

The morphological characteristics are the cap is large, the surface is smooth, hard and crisp, grayish white in color and the stalk is large and round. About 3-15 cm in diameter when blooming, it is shaped like a cone. When it hits the light at night, it glows (Insumran et al., 2016). Can be found during the rainy season in the natural community from May-August in northeastern and northern regions of Thailand.

Figure 15 *Russula delica*.

2.2.4.2 *Phaeogyroporus portentosus*

The general characteristics are mushroom cap is inverted pan shape, large stalk, flowers with oily skin, hard texture, dark brown color (Naksuwankul et al., 2022). Young flowers have fine hairs like brown velvet and approximately 3-15 cm in diameter when grown. Can be found during the rainy season of May-August in Thailand, grows well in dipterocarp forest and deciduous forest.

Figure 16 *Phaeogyroporus portentosus*.

2.2.4.3 *Amanita princeps*

The general characteristics are the cap has a smooth surface without flakes, the flower stalk is hollow along the line (Naksuwankul et al., 2022). Can be found during the rainy season of June-July in northeastern and northern, Thailand, after 2-3 days of new rain in a hot and humid area. It grows well in deciduous forest, mixed forest and dry evergreen forests.

Figure 17 *Amanita princeps*.

2.3 Literature related to efficacy assessment

2.3.1 K-Folds Cross Validation

Evaluation of model performance will determine which model is the most accurate. There are various methods of evaluating efficiency. For example, if there is a large of data, will divide the data into two parts, the first part is used to train model, and the second past for testing. Or if there have little data, some data that train the model will be used to testing.

K-Folds Cross Validation is the division of data into K parts. For example, if K equals 5, if a data set contains 100 images, it is divided into 5 groups of 20 images each. Round 1 uses data set 1 2 3 4 for training and data set 5 for testing.

Round 2 uses data set 1 2 3 5 for training and data set 4 for testing and will continue to do so until all is complete (Firdaus et al., 2018).

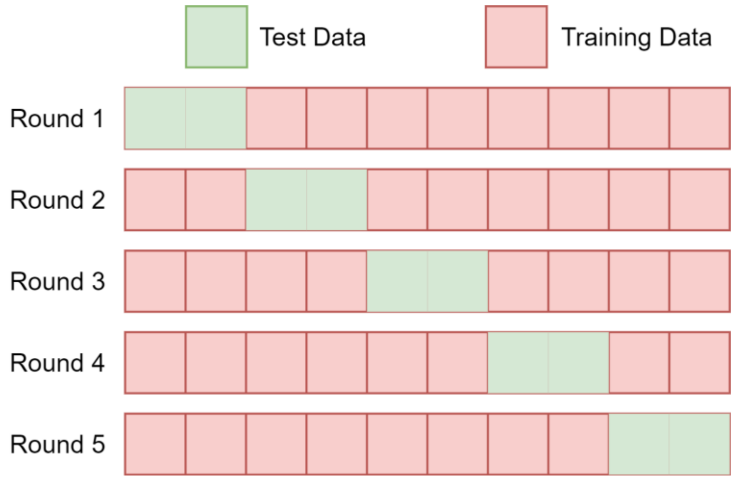

Figure 18 K-Folds Cross Validation.

2.3.2 Confusion Matrix

The Confusion Matrix is a tool for evaluate the performance of the model to determine whether it is effective enough to be developed or used. By measuring the accuracy of the machine learning model prediction with what is actually happening. To evaluate the performance of the model, The authors using F1 score in Equation (2), accuracy in Equation (3), precision in Equation (4), recall in Equation (5) to evaluate the model results. The Confusion matrix is shown in Figure 19.

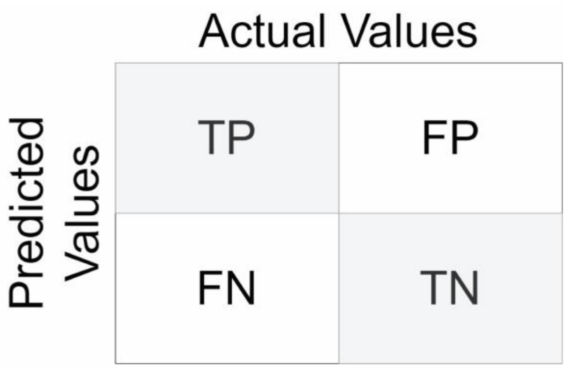

Figure 19 Confusion Matrix. (Ketwongsa et al., 2022)

TP is a True Positive, predict that will come true and it actually happened

TN is a True Negative, predict that will not happen and it didn't happen

FP is a False Positive, predict that will come true but it doesn't happen

FN is a False Negative, predict that will not happen but actually happened.

$$F1Score = 2\frac{Precision \times Recall}{Precision + Recall} \tag{2}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{3}$$

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

$$Recall = \frac{TP}{TP+FN} \tag{4}$$

2.4 Related research

2.4.1 Deep Learning for Oil Palm Fruit Ripeness Classification with DenseNet (Herman et al., 2021). This paper presents the classification of ripeness levels of oil palm fruit by using the convolutional neural network, by compare the performance of two architectures: AlexNet and DenseNet. A total of 400 oil palm fruit dataset were divided into 7 levels of happiness of palm fruit, used for 60% training, 20% validation, and 20% testing. The models were trained for 50 epochs using Stochastic Gradient Descent (SGD) with a 0.001 learning rate, decayed by tenth every eight epochs. Use accuracy, precision, recall, and F1 Score to measure model performance.

Figure 20 Examples of the images in the oil palm fruit dataset. (Herman et al., 2021)

Table 1 The number of images in each class in the dataset.

Class Decription	Number of Images
Ripening	16
Raw	8
Less Ripped	64
Almost Ripped	16
Ripped	96
Perfectly Ripped	168
Too Ripped	32

From the experimental results, it was found that the DenseNet was the most accurate at 86%, Precision 87%, recll 86% and F1 score 86%, followed by Alex Net has accurate at 77%, Precision 78%, recll 77% and F1 score 77%.

2.4.2 Identification of Wild Mushroom Based on Ensemble Learning (Zhao H et al., 2021). This paper presents a performance comparison of four models: VGGNET-16, ResNet-18, GoogLeNet, and Ensemble Model. The wild mushroom dataset consists of 13587 images divided into 27 species. This paper uses data augmentation to increase the amount of data to train the model, The total number of images after data enhancement was 13,587 × 5= 67,938 images. The dataset was divided into training and test sets using a ratio of 90:10 respectively.

Figure 21 Examples of two mushrooms with similar morphology. (Zhao H et al., 2021)

From the experimental results, it was found that Ensemble was the most accurate at 93.92%, precision 93.08% and recall 94.78%, followed by ResNet-18 has accurate at 91.84%, precision 90.82% and recall 92.57%, VGGNET-16 has accurate at 91.60%, precision 90.77% and recall 92.45%, and GoogLeNet has accurate at 90.76%, precision 89.81% and recall 91.73%, respectively.

2.4.3 A Deep Learning-Based Approach for Edible, Inedible and Poisonous Mushroom Classification (Zahan et al., 2021). This paper presents a compare the accuracy of edible, inedible and poisonous mushroom classification for three architectures: InceptionV3, VGG16 and ResNet-50. The mushroom dataset consists of 8,190 images divided into 45 species, used for 80% training and 20% testing.

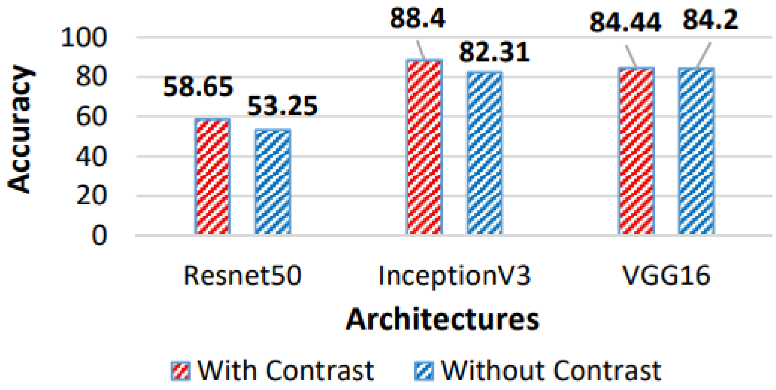

Figure 22 Test accuracy of different transfer learning architecture. (Zahan et al., 2021)

From the experimental results, it was found that VGG16 was the most accurate at 84%, precision 84%, recall 84% and F1 score 84%, followed by InceptionV3 has accurate at 82%, precision 82% and recall 82% and F1 score 82%, ResNet-50 has accurate at 58%, precision 69% and recall 58% and F1 score 53%, respectively. But if using contrast-enhanced images, it was found that InceptionV3 was the most accurate at 88%, precision 88%, recall 88% and F1 score 88%, followed by VGG16 has accurate at 84%, precision 85% and recall 84% and F1 score 85%, ResNet-50 has accurate at 58%, precision 69% and recall 58% and F1 score 58%, respectively.

2.4.4 Research on Fruit Category Classification Based on Convolution Neural Network and Data Augmentation (Zhu et al., 2019). This paper presents a method to fruit category classification based on improved AlexNet convolution neural network. The proposed model is called IANet, IANet consists of 5 convolutional layers four fully connection layers and one output layer. The Fruits-360 dataset consists of 49,561 images divided into 74 types, used for 80% training and 20% testing. This paper uses data augmentation to increase the amount of data to train the model by flip images, rotate images, contrast enhancement, brightness enhancement, and adding Gaussian noise. In the test, the learning rate is 0.01, the number of training iterations is set to 10,000.

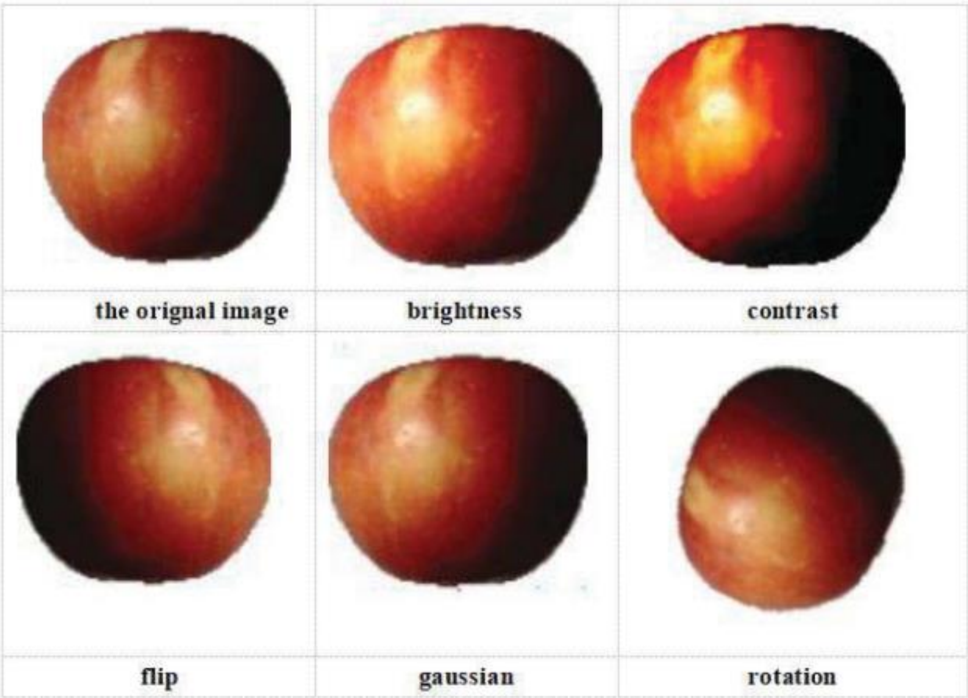

Figure 23 Data augmentation of the Fruits-360 dataset. (Zhu et al., 2019)

From the experimental results, it was found that the proposed model uses the Fruits-360 dataset has accuracy at 98.06% and the proposed model with data enhancement has accuracy at 98.60%.

2.4.5 Classification of Pomelo Leaf Diseases Using Convolution Neural Network (Laosim, Samanchuen, 2021). This paper presents a classification of pomelo leaf diseases using deep learning for three architectures: GoogLeNet, AlexNet and SqueezeNet. Transfer learning was used for classification pomelo leaf diseases, dataset consists of 540 images divided into 183 images of healthy leaves, 107 images of greening leave disease, and 250 images of citrus leafminer, and uses data augmentation to increase the amount of data to train the mode from 540 to 4,320 images.

Figure 24 Example of leaf from dataset: (1) healthy leaves; (2) greening leave disease; (3) citrus leafminer. (Laosim, Samanchuen, 2021)

From the experimental results, it was found that in the case of healthy leaves and citrus leafminer, GoogLeNet was the most accurate at 83.12% in color images, AlexNet was the most accurate at 73.88% and 74.46% in grayscale images and edge detection, respectively.

CHAPTER III
RESEARCH METHODOLOGY

This study is comparative research on methods of classification poisonous and edible mushrooms in Thailand. Which will explain the research process the method of operation is divided into 6 steps as follows:

3.1 Study and review of relevant literature

3.2 Data Collection

3.3 Data preparation

3.4 Modeling

3.5 Research analysis and evaluation

3.1 Study and review of relevant literature

A study and review of the literature related to this research, have studied both in Thailand and abroad that are reliable sources. This research is about comparative methods of classification of poisonous and edible mushrooms in Thailand. Therefore, the literature review will be about neural network, image processing techniques, deep learning AlexNet architecture, GoogLeNet architecture, ResNet-50 architecture to be able to apply knowledge and theory to design and develop an architecture used to classify poisonous and edible mushrooms.

3.2 Data collection

The scope for collecting the image data used in the research is Khon Kaen and Sakon Nakhon, northeast, Thailand. These five species of mushrooms can be found frequently in the northeast of Thailand, certified by Assoc. Prof. Dr. Sophon Boonlue, Department of Microbiology, Khon Kaen University. All mushroom data is divided into five species as follows: first species is *Amanita princeps* 248 images, size 1945 × 3264 pixels, second species is *Phaeogyroporus portentosus* 150 images 1945×3264 pixels, third species is *Inocybe rimosa* 76 images 1945 × 3264 pixels, fourth species is

Amanita phalloides 56 images 1945 × 3264 pixels, fifth species is *Russula delica* 88 images, size 2448 × 3264 pixels. The data collection is shown in Table 2.

Table 2 Mushroom data set.

Species	Mushroom	Amount
1	*Amanita princeps*	248
2	*Phaeogyroporus portentosus*	155
3	*Inocybe rimosa*	76
4	*Amanita phalloides*	56
5	*Russula delica*	88

Figure 25 Sample images of *Amanita princeps*.

Figure 26 Sample images of *Russula delica*.

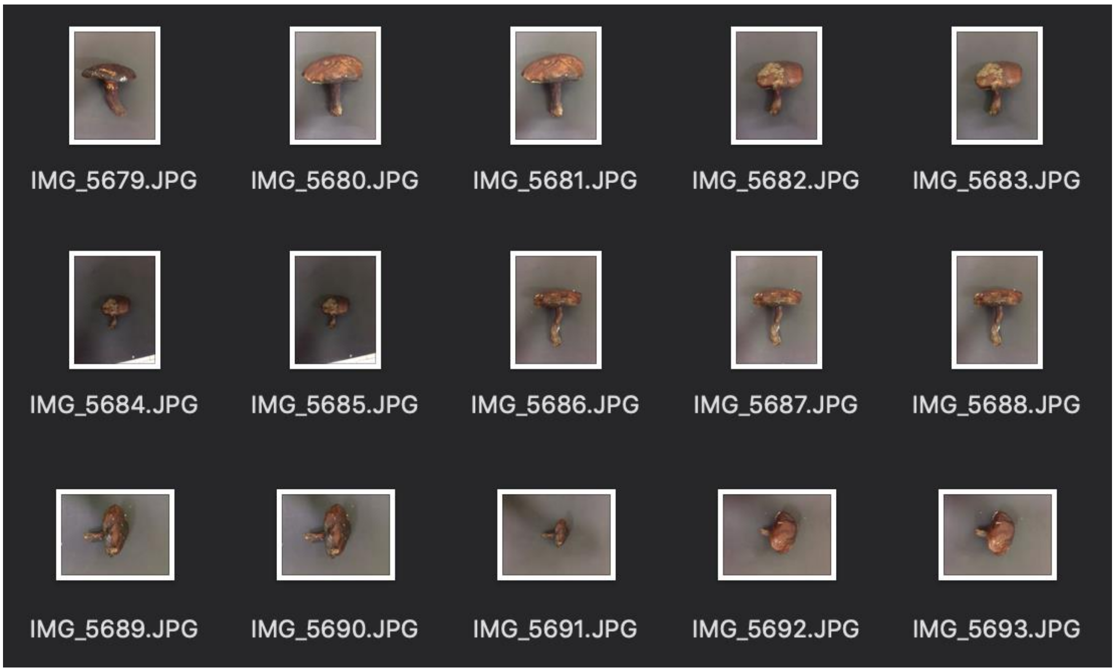

Figure 27 Sample images of *Phaeogyroporus portentosus*.

Figure 28 Sample images of *Amanita phalloides*.

Figure 29 Sample images of *Inocybe rimosa*.

Figure 30 Sample images with different backgrounds.

In Figure 30 shows sample images with different backgrounds, for example: a different colored background, picture of a hand holding a mushroom, a picture with other objects in the picture besides mushrooms, this may affect the accuracy of the classification.

3.3 Data preparation

From the mushroom data collected, all 5 species can be divided into 2 types: poisonous and edible mushrooms. There are three species of edible mushrooms: (A) *Amanita princeps* 248 images, (B) *Russula delica* 88 images, and (C) *Phaeogyroporus portentosus* 155 images, and two species of poisonous mushrooms: (D) *Inocybe rimosa* 76 images, and (E) *Amanita phalloides* 56 images. All images were resized from 2448 $\times 3264$ pixels to 227×227 pixels to match the size of the input layers of the model being training and tested and to speed up processing.

Table 3 Show information about poisonous and edible mushrooms.

Edible			Poisonous	
A	B	C	D	E
248	88	155	76	56

Because the amount of mushroom data is too small. This can lead to large discrepancies in training and testing. Therefore, data augmentation is used to increase the amount of data to train the model. make it more accurate There is less tolerance and can reduce model overfit problems. Data augmentation is to expand image dataset by increase the number of dataset such as flipping images, rotating left/right/top/bottom, contrast enhancement, brightness enhancement (Xu et al., 2022). The original mushroom dataset had 491 edible mushrooms images increased to 1,473, and 132 poisonous mushrooms increased to 527. The original mushroom dataset had 491 edible mushrooms images increased to 1,473 images, and 132 poisonous mushrooms images increased to 527 images. And K-Folds cross-validation was divided into 10 equal groups of 200 images each for training and testing.

Table 4 K-Folds cross-validation.

Group	Amount	Group	Amount
1	200	6	200
2	200	7	200
3	200	8	200
4	200	9	200
5	200	10	200

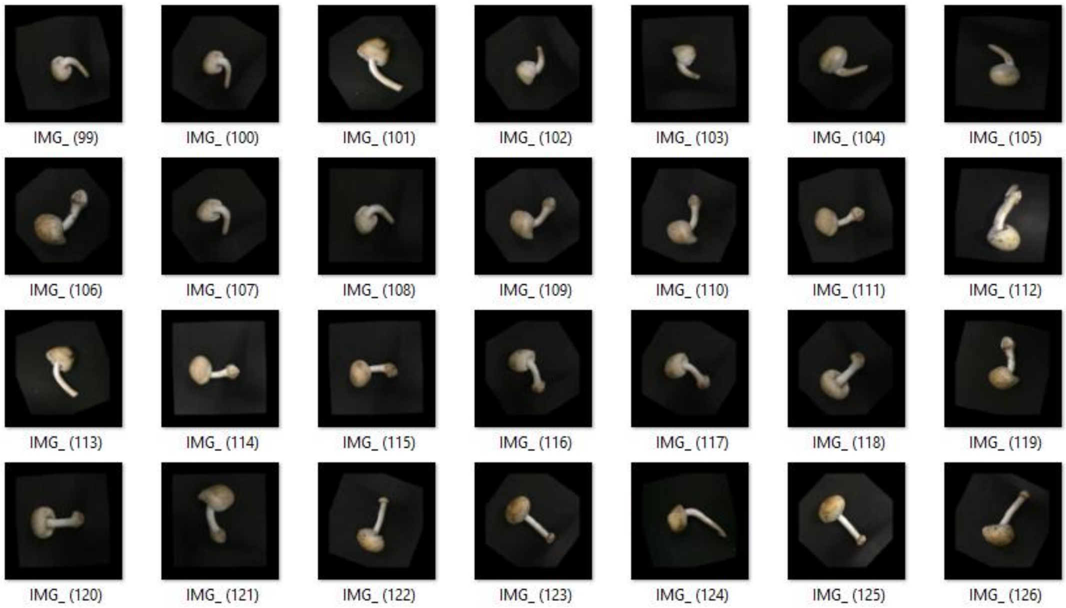

Figure 31 Sample images of *Amanita princeps* after data augmentation.

Figure 32 Sample images of *Russula delica* after data augmentation.

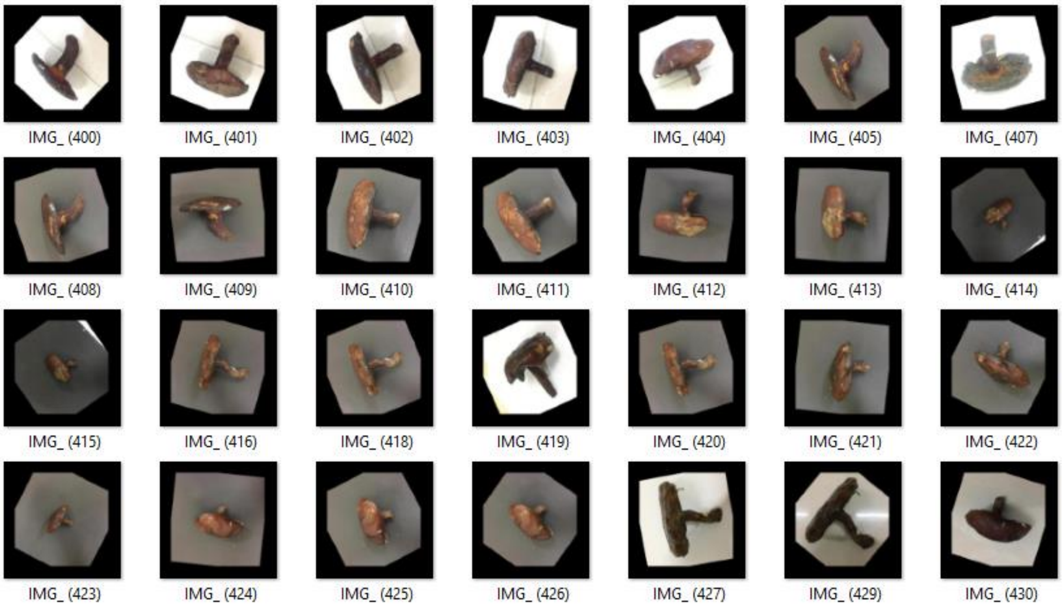

Figure 33 Sample images of *Phaeogyroporus portentosus* after data augmentation.

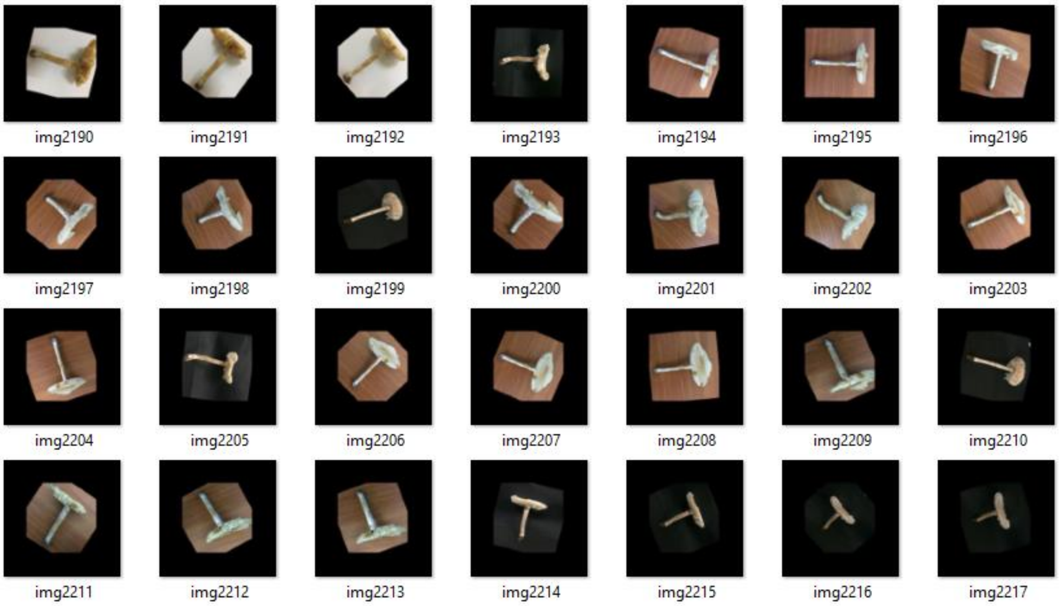

Figure 34 Sample images of *Amanita phalloides* after data augmentation.

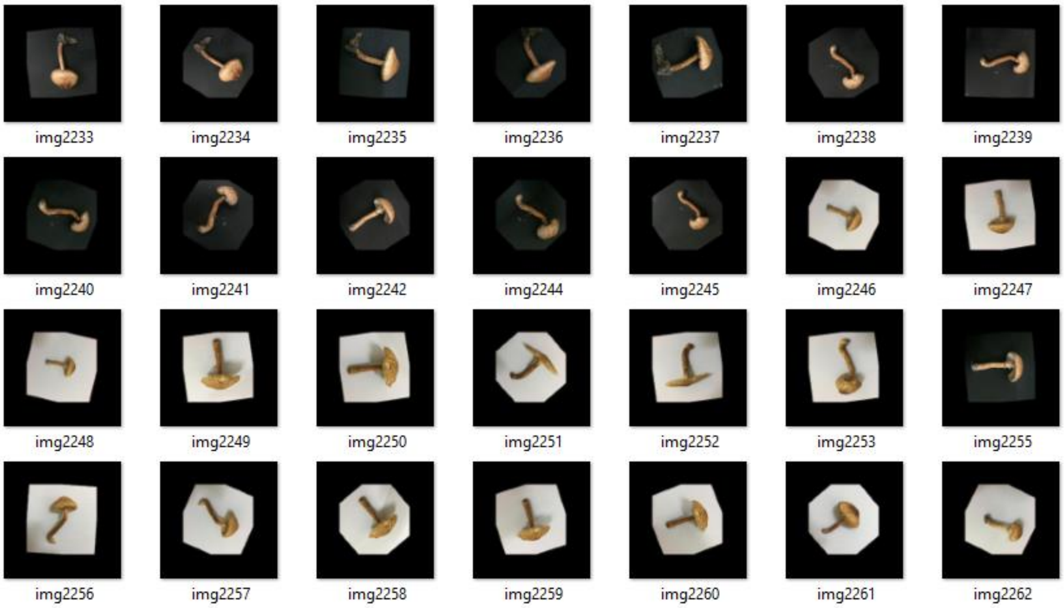

Figure 35 Sample images of *Inocybe rimosa* after data augmentation.

3.4 Modeling

There are two ways to create a model: the first is to create a new model and then do all the training yourself but it need a lot of data to train and take a long time. The second is to take a pre-trained model to transfer learning and adjust to a given task, it can save time training the model because it has been trained on millions of large dataset and multiple classes. In this research, the authors used a second method is to take a pre-trained model to transfer learning and adjust to a given task, there are two methods: convolutional neural networks and region convolutional neural Network. Using three pre-trained models: AlexNet, ResNet-50 and GoogLeNet.

3.4.1 Modeling Convolutional Neural Network

In the experiment convolutional neural network, the fully connected layer is divided into two types: poisonous and edibles mushrooms.

AlexNet transfer learning changes fully connected layer from 1,000 class to 2 class, based on the number of classes of mushroom dataset. Since the Input layer already have an input size of 227 × 227 pixels, there is no need to modify this layer.

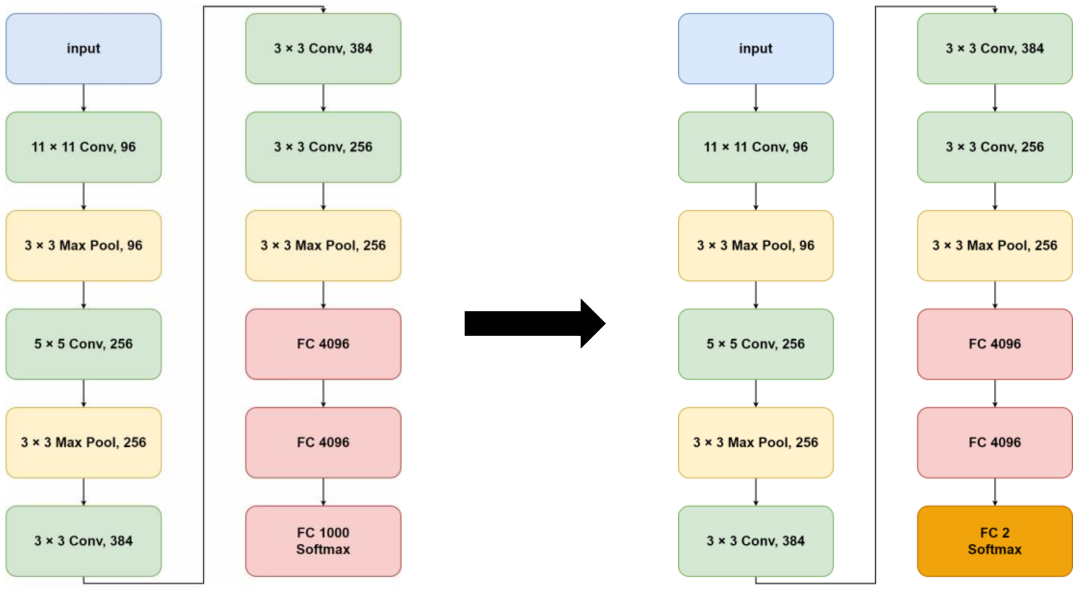

Figure 36 AlexNet transfer learning for CNN.

ResNet-50 transfer learning by changing the Input layer from 224 × 224 pixels to 227 × 227 pixels, and the fully connected layer from 1000 class to 2 class based on the number of classes of mushroom dataset.

Figure 37 ResNet-50 transfer learning for CNN.

GoogLeNet transfer learning by changing the Input layer from 224 × 224 pixels to 227 × 227 pixels, and the fully connected layer from 1000 class to 2 class based on the number of classes of mushroom dataset.

Figure 38 GoogLeNet transfer learning for CNN.

The proposed modal is a new created model based on improve AlexNet architecture, by remove the 4th and 5th convolution layers and add the GoogLeNet inception module instead. And the fully connected layer from 1000 class to 2 class based on the number of classes of mushroom dataset.

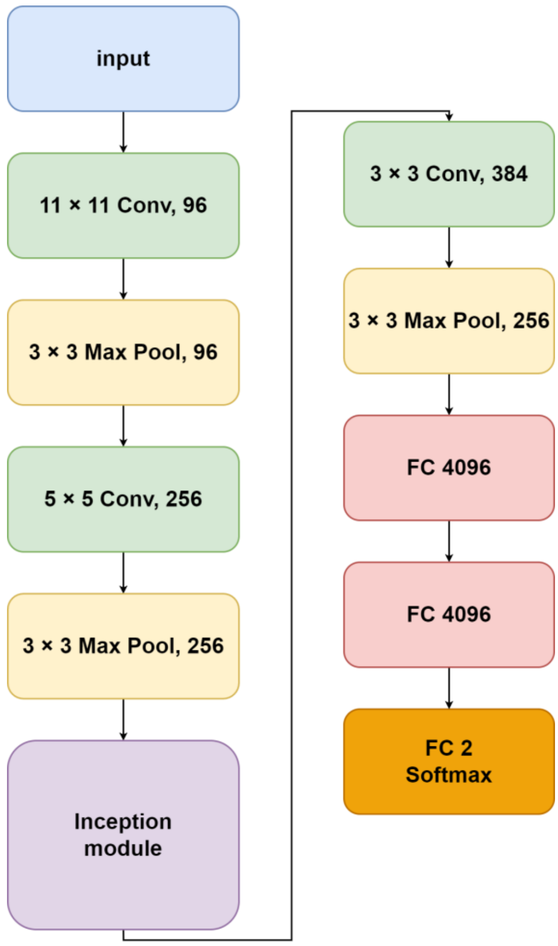

Figure 39 Transfer learning for the proposed model for CNN.

3.4.2 Modeling Region Convolutional Neural Network

In the experiment region convolutional neural network, the fully connected layer is divided into three types: poisonous mushrooms, edibles mushrooms and background.

AlexNet transfer learning changes fully connected layer from 1000 class to 3 class based on the number of classes of mushroom dataset. Since the Input layer already have an input size of 227 × 227 pixels, there is no need to modify this layer.

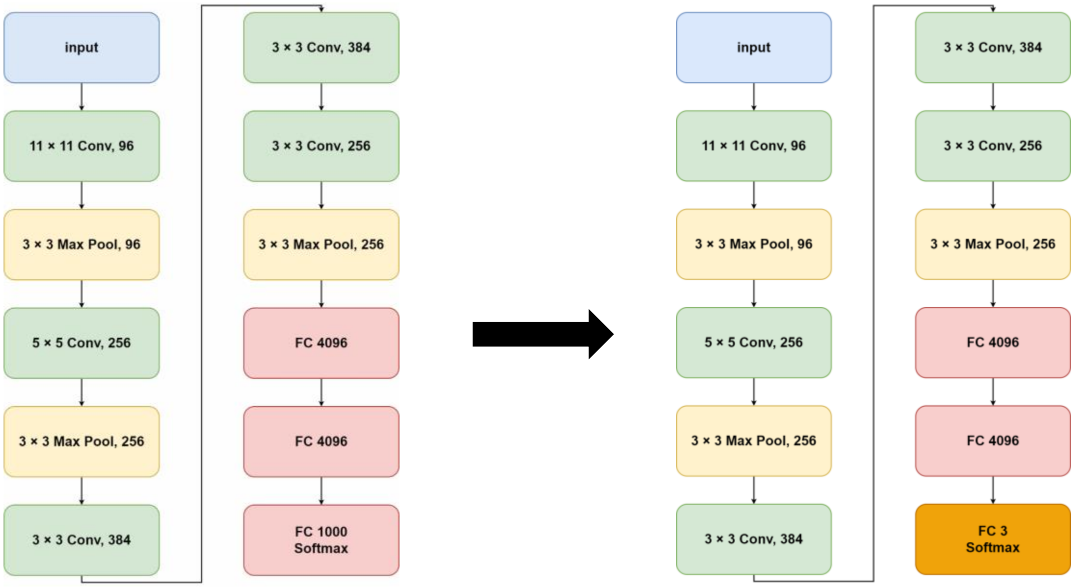

Figure 40 AlexNet transfer learning for R-CNN.

ResNet-50 transfer learning by changing the Input layer from 224 × 224 pixels to 227 × 227 pixels, and the fully connected layer from 1000 class to 3 class based on the number of classes of mushroom dataset.

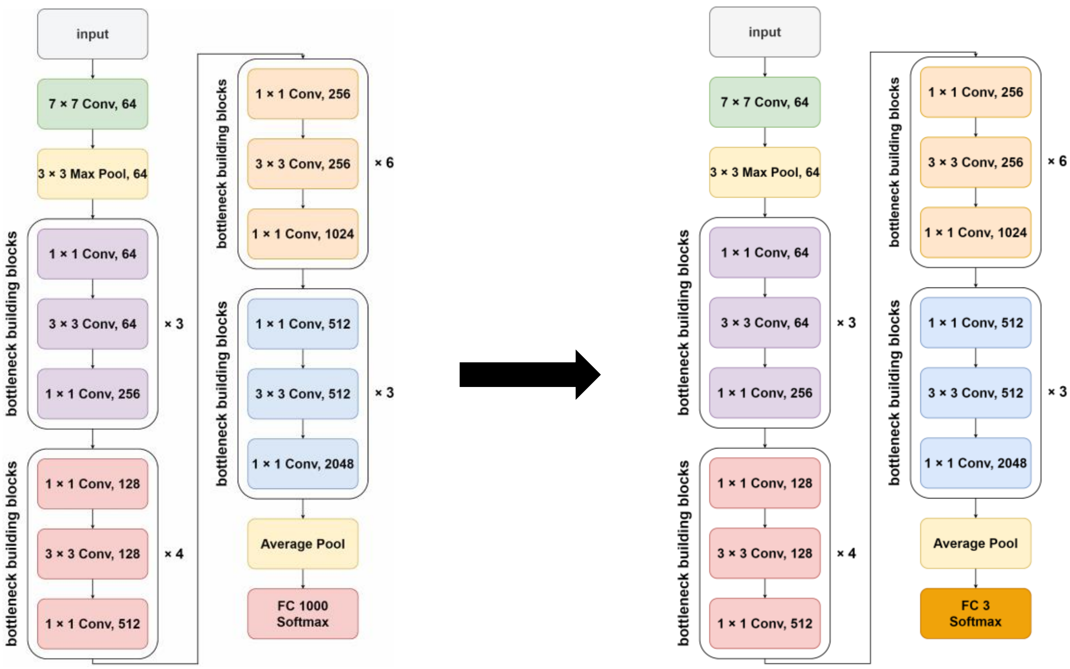

Figure 41 ResNet-50 transfer learning for R-CNN.

GoogLeNet transfer learning by changing the Input layer from 224 × 224 pixels to 227 × 227 pixels, and the fully connected layer from 1000 class to 3 class based on the number of classes of mushroom dataset.

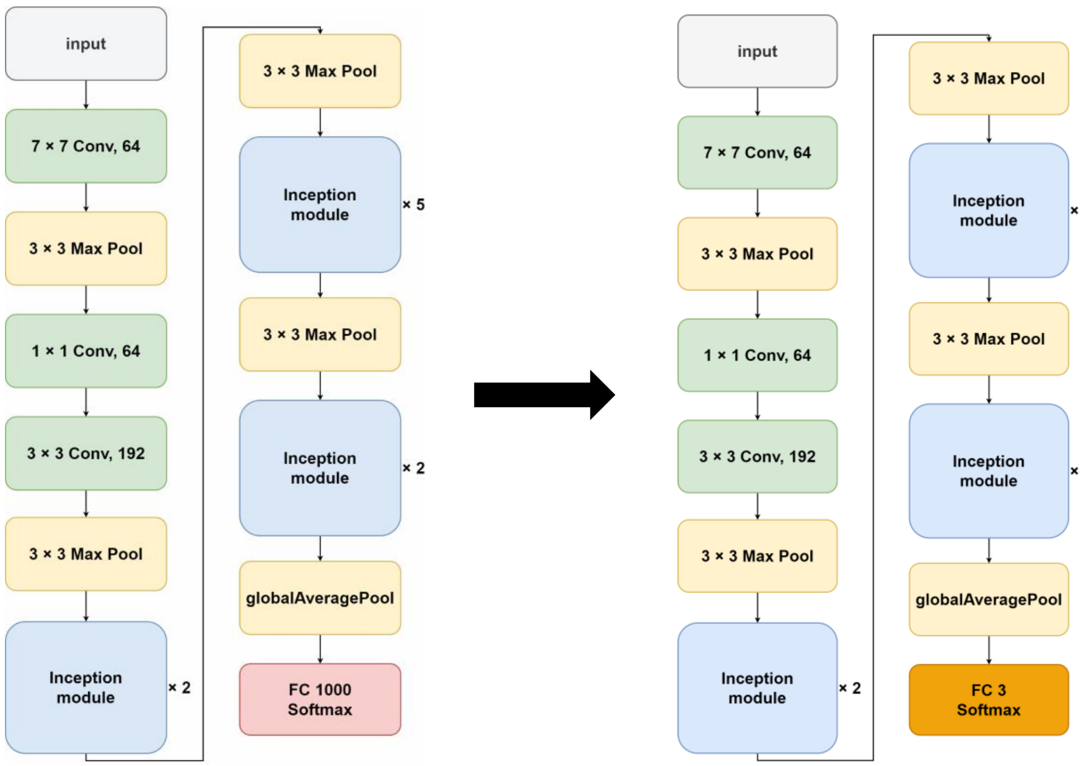

Figure 42 GoogLeNet transfer learning for R-CNN.

The proposed modal is a new created model based on improve AlexNet architecture, by remove the 4th and 5th convolution layers and add the GoogLeNet inception module instead. And the fully connected layer from 1000 class to 3 class based on the number of classes of mushroom dataset.

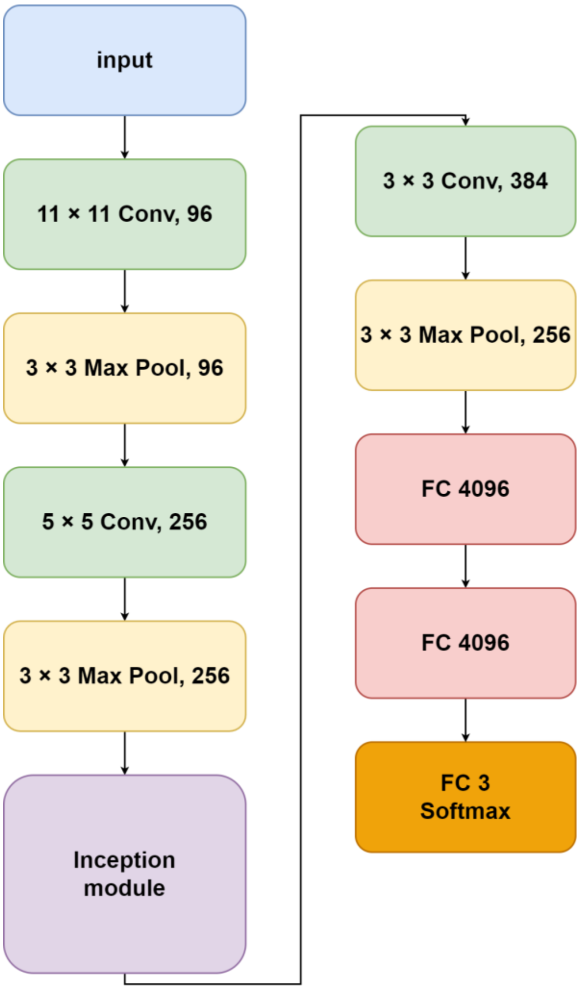

Figure 43 Transfer learning for the proposed model for R-CNN.

3.5 Research analysis and evaluation

In the evaluation phase, the confusion matrix was used to compare the results of each architecture in the classification of poisonous and edible mushrooms, all five species, by comparison with accuracy and testing time. The details of the experimental results are shown in Chapter IV.

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CHAPTER IV
RESULTS

This research uses MATLAB R2021b, Windows 10 64-bit, CPU Intel core i5-12600, RAM 16 GB, GPU NVIDIA GeForce RTX 3060 RAM 12 GB. The experiment was divided into two parts: the classification of poisonous and edible mushrooms using convolutional neural network, and the classification of poisonous and edible mushrooms using region convolutional neural network. Each part of the test used a total of 2,000 images of 227 × 227 pixels in size, divided into 10 sets. The dataset was divided into training and test sets using a ratio of 90:10 respectively.

4.1 Convolutional neural network

Convolutional neural network training must define options for training deep learning neural network, the accuracy and training and testing time will depend on the designation training options. There are three components of the training options: MiniBatchSize, MaxEpochs, and Learning Rate, using a learning rate of 0.001.

4.1.1 AlexNet architecture

Table 5 Experimental results of the number of MiniBatchSize and MaxEpochs of AlexNet architecture for CNN.

MiniBatch Size	MaxEpochs					
	5		7		10	
	Accuracy	Time	Accuracy	Time	Accuracy	Time
20	98.50%	1.13 min	99.00%	1.42 min	99.50%	2.30 min
21	95.50%	1.11 min	100%	1.35 min	98.50%	2.19 min
22	98.50%	1.10 min	97.50%	1.32 min	100%	2.16 min
23	98.50%	1.04 min	100%	1.31 min	99.50%	2.10 min
24	99.00%	1.04 min	99.50%	1.29 min	100%	2.06 min
25	97.50%	1.00 min	100%	1.24 min	99.00%	1.56 min
26	98.50%	1.01 min	99.50%	1.23 min	100%	1.53 min

Table 5 Experimental results of the number of MiniBatchSize and MaxEpochs of AlexNet architecture for CNN (Cont.)

MiniBatch Size	MaxEpochs					
	5		7		10	
	Accuracy	Time	Accuracy	Time	Accuracy	Time
27	99.50%	58 sec	99.00%	1.20 min	99.50%	1.49 min
28	99.00%	55 sec	100%	1.16 min	99.00%	1.46 min
29	99.50%	53 sec	100%	1.14 min	98.50%	1.43 min
30	100%	54 sec	99.00%	1.13 min	99.50%	1.44 min
31	98.50%	53 sec	100%	1.13 min	99.00%	1.42 min
32	98.00%	45 sec	100%	1.01 min	98.50%	1.26 min
33	99.00%	45 sec	95.00%	1.03 min	99.00%	1.28 min
34	100%	44 sec	99.00%	1.02 min	99.00%	1.25 min
35	99.50%	43 sec	100%	1.01 min	98.00%	1.24 min
36	99.00%	43 sec	99.00%	1.00 min	99.00%	1.23 min
37	97.00%	41 sec	99.50%	58 sec	99.00%	1.20 min
38	99.50%	41 sec	100%	56 sec	99.00%	1.18 min
39	98.50%	41 sec	100%	54 sec	99.50%	1.17 min
40	98.50%	39 sec	98.50%	54 sec	99.50%	1.16 min

4.1.2 ResNet-50

Table 6 Experimental results of the number of MiniBatchSize and MaxEpochs of ResNet-50 architecture for CNN.

MiniBatch Size	MaxEpochs					
	5		7		10	
	Accuracy	Time	Accuracy	Time	Accuracy	Time
20	100%	4.40 min	100%	6.31 min	100%	9.35 min
21	100%	4.25 min	99.50%	6.08 min	100%	8.53 min
22	100%	4.19 min	100%	6.01 min	100%	8.52 min
23	99.50%	4.25 min	99.50%	5.54 min	99.50%	8.27 min
24	99.50%	4.19 min	99.50%	5.46 min	100%	8.15 min
25	100%	4.09 min	100%	5.33 min	100%	8.01 min
26	100%	4.02 min	99.50%	5.26 min	100%	7.51 min
27	99.50%	3.57 min	99.00%	5.18 min	100%	7.34 min
28	99.50%	3.47 min	100%	5.05 min	100%	7.24 min
29	100%	3.50 min	99.50%	5.14 min	100%	7.28 min
30	100%	3.44 min	99.50%	5.10 min	100%	7.13 min
31	99.50%	3.42 min	100%	4.59 min	100%	7.10 min
32	99.50%	3.33 min	99.50%	4.42 min	100%	6.58 min
33	100%	3.32 min	100%	4.40 min	100%	6.49 min
34	100%	3.29 min	100%	4.38 min	100%	6.52 min
35	100%	3.34 min	99.50%	4.47 min	100%	6.48 min
36	99.50%	3.34 min	99.50%	4.44 min	100%	6.37 min
37	100%	3.32 min	98.50%	4.39 min	100%	6.38 min
38	100%	3.30 min	99.50%	4.37 min	100%	6.32 min
39	99.50%	3.33 min	99.50%	4.35 min	99.50%	6.24 min
40	99.50%	3.35 min	100%	4.28 min	100%	6.15 min

4.1.3 GoogLeNet

Table 7 Experimental results of the number of MiniBatchSize and MaxEpochs of GoogLeNet architecture for CNN.

MiniBatch Size	MaxEpochs					
	5		7		10	
	Accuracy	Time	Accuracy	Time	Accuracy	Time
20	99.50%	1.51 min	100%	2.37 min	100%	3.38 min
21	99.50%	1.46 min	100%	2.24 min	100%	3.33 min
22	100%	1.43 min	100%	2.24 min	100%	3.26 min
23	99.00%	1.37 min	100%	2.13 min	100%	3.39 min
24	99.50%	1.37 min	100%	2.11 min	100%	3.10 min
25	99.50%	1.31 min	100%	2.05 min	99.50%	3.30 min
26	99.50%	1.30 min	100%	2.03 min	99.50%	2.54 min
27	100%	1.29 min	99.50%	1.58 min	100%	2.50 min
28	99.00%	1.27 min	100%	1.57 min	99.50%	2.54 min
29	99.00%	1.25 min	100%	1.55 min	100%	2.53 min
30	99.00%	1.23 min	99.50%	1.52 min	99.00%	2.58 min
31	99.00%	1.22 min	100%	1.49 min	99.50%	2.56 min
32	99.00%	1.20 min	100%	1.47 min	100%	2.37 min
33	99.50%	1.20 min	99.50%	1.47 min	100%	2.33 min
34	99.50%	1.19 min	99.50%	1.48 min	100%	2.33 min
35	99.00%	1.17 min	100%	1.44 min	100%	2.30 min
36	99.50%	1.16 min	100%	1.43 min	99.50%	2.27 min
37	99.00%	1.12 min	100%	1.38 min	99.50%	2.22 min
38	99.00%	1.11 min	99.50%	1.37 min	99.50%	2.23 min
39	99.00%	1.12 min	100%	1.36 min	99.50%	2.22 min
40	99.00%	1.09 min	100%	1.33 min	99.50%	2.13 min

4.1.4 Proposed Model

Table 8 Experimental results of the number of MiniBatchSize and MaxEpochs of proposed architecture for CNN.

MiniBatch Size	MaxEpochs					
	5		7		10	
	Accuracy	Time	Accuracy	Time	Accuracy	Time
20	99.00%	1.19 min	100%	1.41 min	98.50%	2.18 min
21	99.00%	1.10 min	99.50%	1.33 min	99.50%	2.13 min
22	97.50%	1.08 min	99.00%	1.29 min	99.50%	2.08 min
23	100%	1.03 min	98.50%	1.26 min	99.00%	2.05 min
24	99.00%	1.04 min	99.50%	1.24 min	98.00%	2.00 min
25	88.00%	1.04 min	98.50%	1.23 min	98.00%	1.58 min
26	94.00%	1.02 min	99.50%	1.18 min	98.00%	1.53 min
27	99.50%	1.03 min	98.50%	1.15 min	98.50%	1.48 min
28	98.50%	1.00 min	99.00%	.112 min	99.00%	1.42 min
29	97.50%	55 sec	99.00%	1.11 min	99.00%	1.40 min
30	99.50%	52 sec	98.00%	1.12 min	98.50%	1.41 min
31	98.00%	51 sec	99.50%	1.11 min	99.00%	1.36 min
32	98.50%	42 sec	99.50%	58 sec	98.50%	1.21 min
33	98.50%	42 sec	99.50%	59 sec	99.00%	1.27 min
34	100%	41 sec	98.50%	59 sec	98.50%	1.23 min
35	98.00%	41 sec	99.50%	58 sec	98.00%	1.19 min
36	98.00%	41 sec	99.50%	56 sec	98.50%	1.23 min
37	98.50%	40 sec	98.50%	54 sec	98.50%	1.18 min
38	99.00%	39 sec	100%	53 sec	100%	1.19 min
39	97.50%	39 sec	99.50%	54 sec	100%	1.16 min
40	98.50%	38 sec	100%	53 sec	98.50%	1.14 min

From the above experiment, the author chose to use MiniBatchSize at 38, MaxEpochs at 5, because it has high accuracy and fastest training time.

Table 9 Parameters used in CNN training.

Parameters	Architecture			
	AlexNet	ResNet-50	GoogLeNet	Proposed
Learning rate	0.001	0.001	0.001	0.001
MaxEpochs	5	5	5	5
MiniBatchSize	38	38	38	38

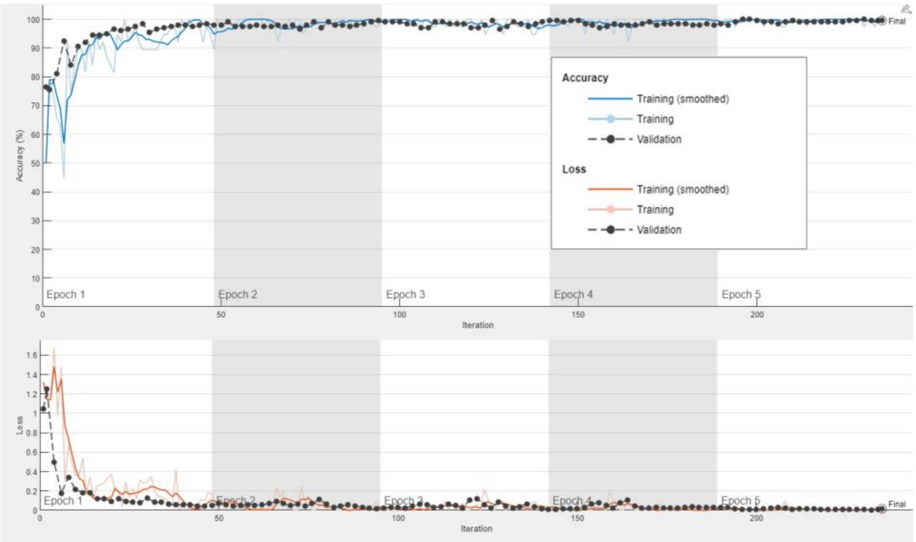

Figure 44 Training results AlexNet.

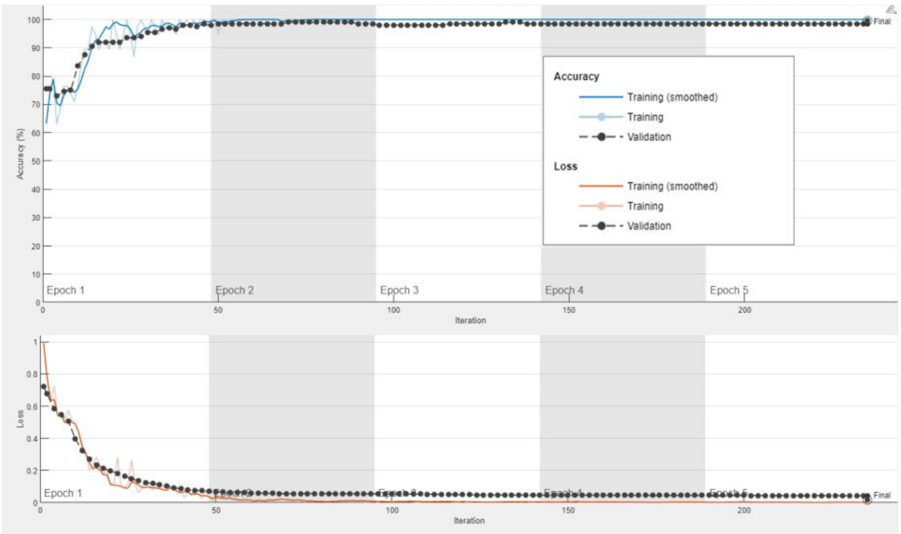

Figure 45 Training results ResNet-50.

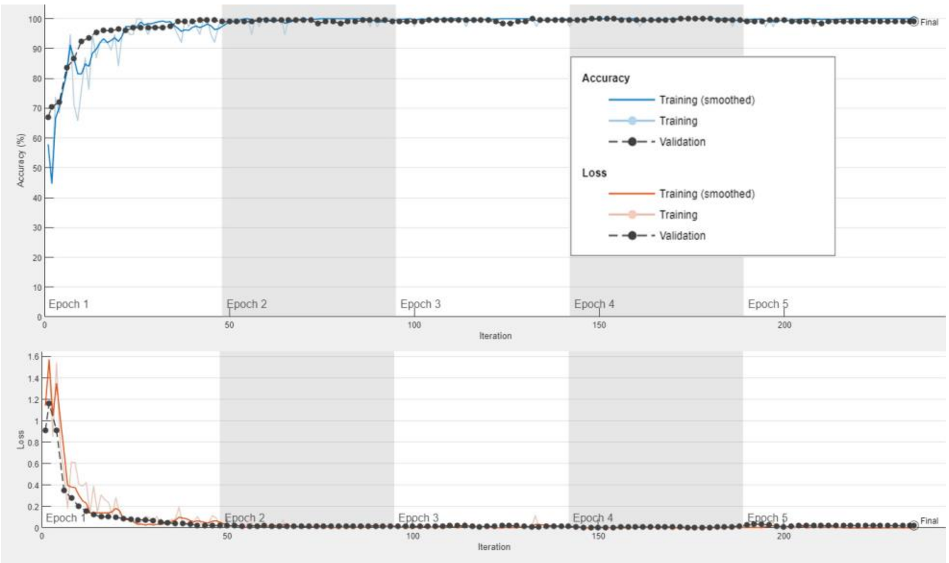

Figure 46 Training results GoogLeNet.

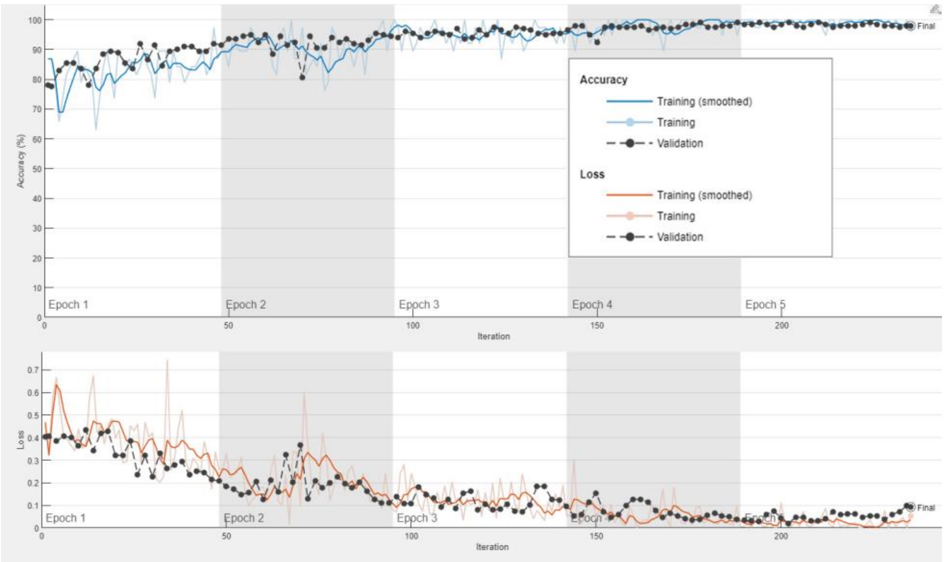

Figure 47 Training results Proposed model.

From Figure 44 – Figure 47 showing the results of training and validation. Dark blue line is the classification accuracy in each mini-batch, black dotted line is the accuracy of the classification in the entire check set. Figure 44 Alexnet architecture has a stable validation after 40 iterations with a training accuracy at 99.00%. Figure 45 ResNet-50 architecture has a stable validation after 50 iterations with a training accuracy at 99.50%. Figure 46 GoogLeNet architecture has a stable validation after 40 iterations with a training accuracy at 99.50%. And Figure 47 Proposed architecture has a stable validation after 150 iterations with a training accuracy at 99.00%.

		Target Class Proposed	
		Edible	Poisonous
Output	Edible	149	0
	Poisonous	2	49

(a)

		Target Class AlexNet	
		Edible	Poisonous
Output	Edible	146	0
	Poisonous	2	52

(b)

		Target Class GoogLeNet	
		Edible	Poisonous
Output	Edible	146	1
	Poisonous	0	53

(c)

		Target Class ResNet-50	
		Edible	Poisonous
Output	Edible	157	1
	Poisonous	0	42

(d)

Figure 48 The confusion matrix of the CNN analysis: (a) proposed model; (b) AlexNet; (c) GoogLeNet; (d) ResNet-50.

As is shown in Figure 48, the proposed has an accuracy of 99.00%, precision of 100%, recall of 98.68%, an F1 score of 99.33%, and a training time of 40 seconds. AlexNet has an accuracy of 99.00%, precision of 100%, recall of 98.65%, an F1 score of 99.32%, and a training time of 46 seconds. GoogLeNet has an accuracy of 99.50%, precision of 99.32%, recall of 100%, an F1 score of 99.66%, and a training time of 1.13 minutes. ResNet-50 has an accuracy of 99.50%, precision of 99.37%, recall of 100%, an F1 score of 99.68%, and a training time of 3.23 minutes.

4.2 Region convolutional neural networks

Region convolutional neural networks training must define options for training deep learning neural network, the accuracy and training and testing time will depend on the designation training options. There are three components of the training options: MiniBatchSize, MaxEpochs, and Learning Rate, using a learning rate of 0.001.

4.2.1 AlexNet

Table 10 Experimental results of the number of MiniBatchSize and MaxEpochs of AlexNet architecture for R-CNN.

MiniBatchSize	MaxEpochs			
	1		2	
	Accuracy	Time	Accuracy	Time
20	97.00%	4.28 min	94.50%	8.56 min
21	96.50%	4.42 min	95.50%	8.57 min
22	96.50%	4.25 min	93.50%	8.40 min
23	94.00%	4.19 min	93.50%	8.23 min
24	94.50%	4.15 min	95.50%	8.05 min
25	95.00%	4.20 min	95.00%	8.25 min
26	95.00%	4.12 min	95.00%	8.16 min
27	95.50%	4.07 min	94.50%	7.57 min
28	96.00%	3.56 min	93.00%	7.46 min
29	90.00%	4.04 min	93.50%	7.57 min
30	96.00%	4.10 min	96.00%	8.11 min

4.2.2 ResNet-50

Table 11 Experimental results of the number of MiniBatchSize and MaxEpochs of ResNet-50 architecture for R-CNN.

MiniBatchSize	MaxEpochs			
	1		2	
	Accuracy	Time	Accuracy	Time
20	96.00%	13.44 min	96.00%	27.25 min
21	95.50%	14.04 min	97.00%	27.41 min
22	96.00%	13.42 min	95.50%	27.03 min
23	96.00%	13.25 min	96.50%	26.59 min
24	95.50%	13.01 min	95.50%	26.00 min

Table 11 Experimental results of the number of MiniBatchSize and MaxEpochs of ResNet-50 architecture for R-CNN (Cont.)

MiniBatchSize	MaxEpochs			
	1		2	
	Accuracy	Time	Accuracy	Time
25	96.00%	12.59 min	96.00%	25.45 min
26	96.50%	12.57 min	96.00%	25.23 min
27	96.50%	13.00 min	95.50%	25.26 min
28	94.50%	12.39 min	97.00%	24.54 min
29	95.50%	12.39 min	96.50%	24.53 min
30	95.50%	12.40 min	96.00%	25.06 min

4.2.3 GoogLeNet

Table 12 Experimental results of the number of MiniBatchSize and MaxEpochs of GoogLeNet architecture for R-CNN.

MiniBatchSize	MaxEpochs			
	1		2	
	Accuracy	Time	Accuracy	Time
20	96.50%	6.32 min	93.50%	13.00 min
21	94.50%	6.40 min	96.00%	13.13 min
22	96.00%	6.28 min	94.00%	12.28 min
23	93.50%	6.18 min	93.50%	12.16 min
24	94.50%	6.09 min	93.00%	11.56 min
25	93.00%	6.07 min	95.00%	12.10 min
26	96.00%	6.02 min	95.00%	12.01 min
27	94.00%	6.02 min	94.00%	11.45 min
28	92.50%	6.01 min	92.50%	11.31 min
29	96.00%	6.04 min	94.50%	12.02 min
30	93.00%	6.04 min	94.00%	12.17 min

4.2.4 Proposed Model

Table 13 Experimental results of the number of MiniBatchSize and MaxEpochs of proposed architecture for R-CNN.

MiniBatchSize	MaxEpochs			
	1		2	
	Accuracy	Time	Accuracy	Time
20	95.00%	4.37 min	95.00%	8.59 min
21	94.50%	4.35 min	93.50%	9.11 min
22	94.50%	4.15 min	97.00%	8.34 min
23	93.00%	4.06 min	93.50%	8.12 min
24	90.50%	3.55 min	94.00%	7.58 min
25	92.00%	4.04 min	94.00%	8.10 min
26	95.00%	3.55 min	93.50%	7.52 min
27	92.50%	3.45 min	94.50%	7.37 min
28	95.00%	3.46 min	94.50%	7.25 min
29	92.00%	3.59 min	95.00%	7.46 min
30	90.00%	3.58 min	96.00%	7.59 min

From the above experiment, the author chose to use MiniBatchSize at 26, MaxEpochs at 1, because it is the parameters that each architecture takes the least time and provides high accuracy, but not the most accuracy for each architecture.

Table 14 Parameters used in R-CNN training.

Parameters	Architecture			
	AlexNet	ResNet-50	GoogLeNet	Proposed
Learning rate	0.001	0.001	0.001	0.001
MaxEpochs	1	1	1	1
MiniBatchSize	26	26	26	26

		Target Class Proposed	
		Edible	Poisonous
Output	Edible	141	6
	Poisonous	2	51

(a)

		Target Class AlexNet	
		Edible	Poisonous
Output	Edible	144	4
	Poisonous	1	51

(b)

		Target Class GoogLeNet	
		Edible	Poisonous
Output	Edible	141	8
	Poisonous	0	51

(c)

		Target Class ResNet-50	
		Edible	Poisonous
Output	Edible	138	9
	Poisonous	0	53

(d)

Figure 49 The confusion matrix for the R-CNN analysis: (a) proposed model; (b) AlexNet; (c) GoogLeNet; (d) ResNet-50.

As is shown in Figure 49, the proposed has an accuracy of 96.00%, precision of 95.92%, recall of 98.60%, an F1 score of 97.24%, and a training time of 4.05 minutes. AlexNet has an accuracy of 97.50%, precision of 97.30%, recall of 99.31%, an F1 score of 98.29%, and a training time of 4.15 minutes. GoogLeNet has an accuracy of 96.00%, precision of 94.63%, recall of 100%, an F1 score of 97.24%, and a training time of 5.59 minutes. ResNet-50 has an accuracy of 95.50%, precision of 93.88%, recall of 100%, an F1 score of 96.84%, and a training time of 12.46 minutes.

Table 15 The most accurate parameter used in R-CNN training.

Parameters	Architecture			
	AlexNet	ResNet-50	GoogLeNet	Proposed
Learning rate	0.001	0.001	0.001	0.001
MaxEpochs	2	2	3	2
MiniBatchSize	26	26	26	26

		Target Class Proposed	
		Edible	Poisonous
Output	Edible	145	2
	Poisonous	2	51

(a)

		Target Class AlexNet	
		Edible	Poisonous
Output	Edible	143	4
	Poisonous	0	53

(b)

		Target Class GoogLeNet	
		Edible	Poisonous
Output	Edible	141	6
	Poisonous	0	53

(c)

		Target Class ResNet-50	
		Edible	Poisonous
Output	Edible	143	4
	Poisonous	0	53

(d)

Figure 50 The confusion matrix for the R-CNN analysis at maximum accuracy: (a) proposed model; (b) AlexNet; (c) GoogLeNet; (d) ResNet-50.

As is shown in Figure 50, it is the most accuracy for each architecture, the proposed has an accuracy of 98.00%, precision of 98.64%, recall of 98.64%, an F1 score of 98.64%, and a training time of 7.47 minutes. AlexNet has an accuracy of 98.00%, precision of 97.28%, recall of 100%, an F1 score of 98.62%, and a training time of 8.17 minutes. GoogLeNet has an accuracy of 97.00%, precision of 95.92%, recall of 100%, an F1 score of 97.92%, and a training time of 17.51 minutes. ResNet-50 has an accuracy of 98.00%, precision of 97.28%, recall of 100%, an F1 score of 98.62%, and a training time of 25.18 minutes.

CHAPTER V
DISCUSSION AND CONCLUSION

5.1 Conclusions

In this research, the authors compared the classification accuracy of poisonous and edible mushrooms for CNN and R-CNN methods of four architectures: AlexNet, ResNet-50, GoogLeNet and proposed model.

Table 16 CNN test results.

Architecture	Accuracy	Time
Proposed Model	99.00%	40 sec
AlexNet	99.00%	46 sec
GoogLeNet	99.50%	1.13 min
ResNet-50	99.50%	3.23 min

From table 16, in the classification mushrooms using CNN. The architecture that takes the least training time is proposed model had a training time of 40 seconds and accuracy of 99.00%. Followed by AlexNet had a training time of 46 seconds and accuracy of 99.00%, and GoogLeNet and ResNet-50 have the most accuracy of 99.50%, training time of 1.13 minutes and 3.23 minutes, respectively.

Table 17 R-CNN test results.

Architecture	Accuracy	Time
Proposed Model	98.00%	7.47 min
AlexNet	98.00%	8.17 min
GoogLeNet	97.00%	17.51 min
ResNet-50	98.00%	25.18 min

From table 17, in the classification mushrooms using R-CNN, compare the time from the most accuracy of each architecture. The architecture that takes the least training time is the proposed model that has a training time of 7.47 minutes and accuracy of 98.00%. Followed by AlexNet had a training time of 8.17 minutes and accuracy of 98.00%, GoogLeNet had a training time of 17.51 minutes and accuracy of 97.00%, and ResNet-50 had a training time of 25.18 minutes and accuracy of 98.00%.

From the experimental results, the proposed model can accurately classify poisonous and edible mushrooms, and also shorten training and testing times.

5.2 Suggestion

In the future, this research can be developed further, such as Increasing the number of data sets used for training, increasing the number of mushroom species to be more diverse in order to be able to classify all species, and different background images taken in different environments with other objects in the picture besides mushrooms. In order to allow the model to classify images with more complexity and with fewer errors.

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