Mushroom Classification using Convolutional Neural Network

Imee Compra, Sophia Dalumpines, Christine delos Reyes, Lea Flor
College of Science, Technological University of the Philippines - Manila
imee.compra@tup.edu.ph
sophia.dalumpines@tup.edu.ph
christine.delosreyes@tup.edu.ph
lea.flor@tup.edu.ph

Abstract – Mushrooms are a fungus that comes in different sizes, shapes, and colors. They can be found even in the most obscure places. They thrive in absorbing nutrients from decaying organic matter. Nowadays, mushrooms have been popular as a valuable food source because it is low in calories, cholesterol free, and have a lot more benefits. However, it is not easy to determine whether a mushroom is edible or not. This project will present the distinction between the edibility of mushrooms using Convolutional Neural Network.

Keywords: *Fungus, Convolutional Neural Network, Genus, Mushroom*

I. INTRODUCTION

A mushroom is a prevalent fungal fruiting body with high protein content. Typically, it is created on the soil surface or in conjunction with other fertilizers. It supports weight loss, immune system improvement, and cancer prevention. There are tens of thousands of different types of mushrooms in existence [1].

Traditionally, picking mushrooms has been a very common pastime for many people. However, due to the huge number of species, similarity in appearance, and the broad spectrum of environmental impacts during imaging, image-based mushroom recognition poses a significant challenge for machine learning algorithms [2].

The majority of the existing techniques for identifying mushrooms still rely on detection and experience-based observation of the mushroom's picture. However, convolutional neural networks have progressively begun to be used for mushroom recognition due to the rapid advancement of deep learning [3].

Because it is effective at handling issues with object categorization and recognition and has greatly improved the accuracy of many machine learning tasks, the convolution neural network (CNN) developed in the past has been extensively employed in the field of image processing. It has evolved into a prevalent and accepted deep learning model [4].'

In this study, the focus is on developing and evaluating a convolutional neural network classification model for mushrooms.

II. RELATED WORK

[5] Convolutional Neural Networks or CNNs are a type of deep neural network that are specifically designed to analyze inputs with a spatial structure. CNNs are mainly applied to computer vision problems, such as self-driving cars, robotics, drones, security, medical diagnoses, and treatments for the visually impaired, by utilizing images as inputs. This is due to the fact that CNNs can effectively handle the grid-like structure of image data. CNNs function by extracting low-level features such as edges and points and then combining these to form higher-level representations like shapes and contours. The term "convolutional" in the name of these deep neural networks refers to the use of convolutions, a type of linear mathematical operation, in their processing. Compared to other classification algorithms, CNNs require less preprocessing. This is one of the reasons why CNNs have been utilized for tasks such as face recognition, identification of individuals, tumor detection, object recognition, and identifying street signs, among others. CNNs are deep neural networks that can make use of both the high computing power and large data sets that are readily available in many fields today. Additionally, CNNs eliminate the requirement of explicitly determining which inputs (independent variables) to include in the analysis. This is because they optimize the entire process of mapping data samples to outputs that are aligned with the large, labeled data sets used in training the deep neural network.

[6] A Convolutional Neural Network typically consists of three different types of processing layers: convolution layer, pooling layer, and full connection layer. The convolution layer performs the feature extraction task, while the pooling layer

performs feature mapping. The full connection layer resembles a typical neural network structure, where all nodes in this layer are fully connected to the nodes of the previous layer, but not connected. Just like other neural networks, Convolutional Neural Networks also has a data input layer and a result output layer. The main computational task in a Convolutional Neural Network is carried out through the convolution layer, where the convolution kernel acts as the core of the CNN model. The convolution layer employs a convolution operation to process the input image and extract its characteristic information. As a result of the convolution operation, the images become smaller and the pixels at the edges have minimal impact on the output. There is typically a strong relationship between adjacent pixels in an image, and the convolution kernel extracts features from the local region of the image and transfers these features to higher levels for further processing. Since the low-level features of an image are independent of its position, the same convolution operation can be used to extract relevant features, and the number of parameters in the neural network can be reduced through the shared weight characteristic of the convolution kernel, thereby enhancing the training efficiency of the network. For more complex images, the pooling layer in a Convolutional Neural Network can be utilized to reduce the size of the feature map and reduce the amount of model parameter training. During pooling, the depth and size of the image remain unchanged. The pooling layer typically employs either max pooling or average pooling. [7] The main advantage of using deep learning for object recognition is its ability to perform feature extraction with a deep neural network. This eliminates the need for manual feature design and leads to better feature expression and recognition accuracy. Deep learning algorithms are trained on large and diverse data, allowing for a comprehensive extraction of image features and the creation of a robust recognition model. These algorithms exhibit high stability, strong generalization ability, and better recognition results compared to traditional algorithms, making them well-suited for real-world applications.

[8] The detection and classification of distinct fungal species using a deep convolutional neural network can effectively and efficiently boost production efficiency. However, there are numerous types of mushrooms, and their impact on the living environment is enormous. Mushroom identification is a difficult task, and

traditional convolutional neural network models typically have a large number of variables and are not deployed on communication systems. In their experiment, There are various articles on the efficiency of CNNs for specific issues, for instance [9, 2]. They believe that their experiments and ideas provide useful information to others, not just in the instance of mushroom photos. According to the experiment, [11] the suggested model can categorize all 45 species of mushrooms with high accuracy, and it is resilient in scaling, translation, rotation, light condition, and perspective transform, which are the study's problem points.

III. EXPERIMENT

A. Data Collection

The researchers gathered images of the following mushroom genus to use as a dataset: Cortinarius, Lactarius, and Russula. 4925 mushroom images were garnered for Cortinarius, 3650 images for Lactarius, and 5036 images for Russula.

The dataset was split into two: 10899 were used for training and 2722 for validation. In total, 13,611 mushroom images were gathered as a dataset.

B. Convolutional Neural Network

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 sequential (Sequential)     (None, 224, 224, 3)       0

 rescaling_2 (Rescaling)     (None, 224, 224, 3)       0

 conv2d (Conv2D)             (None, 224, 224, 16)      448

 max_pooling2d (MaxPooling2D  (None, 112, 112, 16)     0
 )

 conv2d_1 (Conv2D)           (None, 112, 112, 32)      4640

 max_pooling2d_1 (MaxPooling  (None, 56, 56, 32)       0
 2D)

 conv2d_2 (Conv2D)           (None, 56, 56, 64)        18496

 max_pooling2d_2 (MaxPooling  (None, 28, 28, 64)       0
 2D)

 conv2d_3 (Conv2D)           (None, 28, 28, 128)       73856

 max_pooling2d_3 (MaxPooling  (None, 14, 14, 128)      0
 2D)

 conv2d_4 (Conv2D)           (None, 14, 14, 256)       295168

 max_pooling2d_4 (MaxPooling  (None, 7, 7, 256)        0
 2D)

 dropout (Dropout)           (None, 7, 7, 256)         0

 flatten (Flatten)           (None, 12544)             0

 dense (Dense)               (None, 128)               1605760

 dense_1 (Dense)             (None, 3)                 387

=================================================================
Total params: 1,998,755
Trainable params: 1,998,755
Non-trainable params: 0
_________________________________________________________________
```

Figure 1. Model Summary

Convolutional Neural Network (CNN) is a deep learning algorithm used to analyze visual imagery. With the help of CNN, Computer Vision has seen exponential advancements.

Applying CNN to this project, the proposed system has a 17 layers-deep model to classify mushroom images into their respective genus.

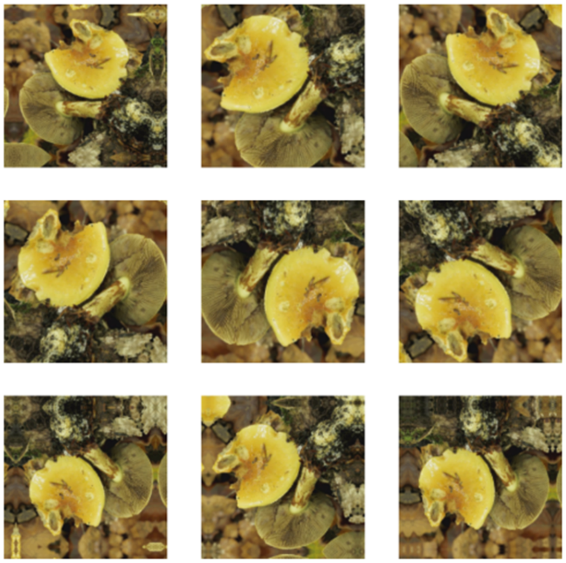

Figure 2. Data Augmentation

In the first two layers, the dataset is preprocessed. The first layer is normalization, wherein each of the images will be rescaled. Each scale pixel values from the range [0, 255] to the range [0, 1]. The second layer is augmentation, in here the images are going to be augmented. In this layer, data augmentation is performed using a Sequential model composed of three operations: RandomFlip, RandomRotation, and RandomZoom, as shown in Figure 2.

After preprocessing the dataset, it will now enter the 13 deep-layer convolutional neural networks. The convolutional layers of the model use the relu activation function and max pooling to reduce the spatial dimensions of the data.

The model has one dropout layer to reduce overfitting in neural networks. Moreover, this helps to prevent the model from memorizing the training data, instead encouraging it to learn a more general representation of the data.

Lastly, the images will enter the two-layer deep dense layer, where final predictions of the model are made.

C. User Interface and Testing

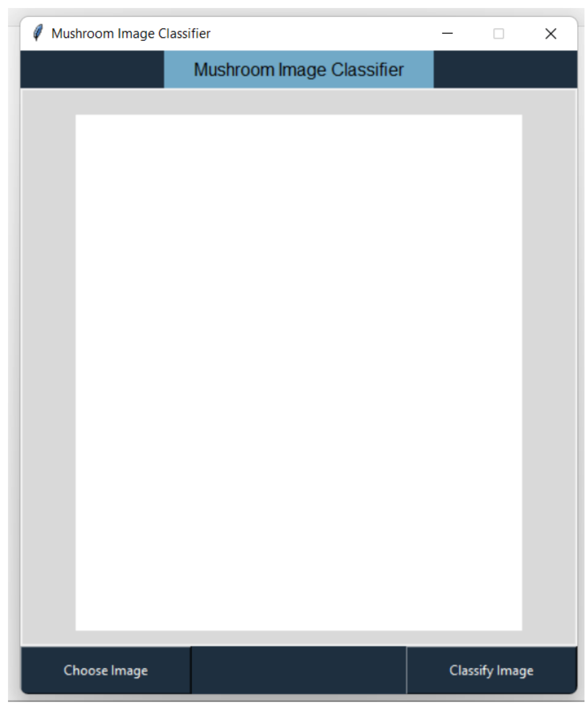

Figure 3. User Interface of the System

In order to deploy the CNN model, the proposed system utilized Tkinter. Tkinter is the standard method for creating graphical user interfaces (GUIs) in Python and is included in all standard distributions of the language.

To test the performance of the model, the researchers test 10 images per data class, 30 test images in total.

IV. RESULTS

A. Training Result

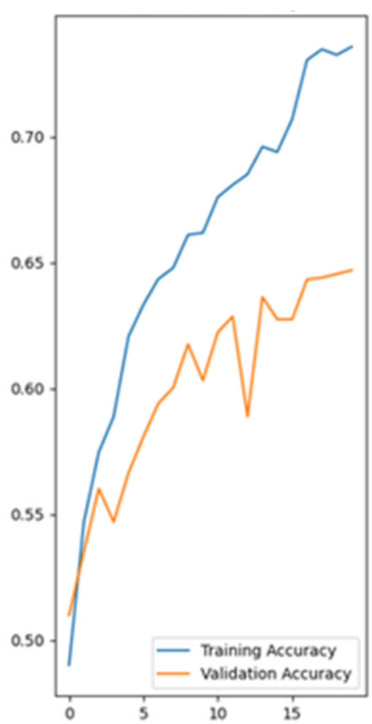

Figure 4. Model accuracy

Figure 3 shows the result upon training the dataset. At epoch 20, the model achieves 73.57% training accuracy and 64.7% validation accuracy.

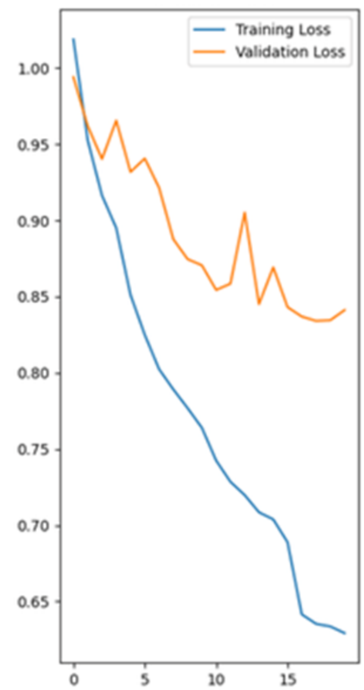

Figure 5. Model loss

In terms of loss, the model yields 62.92% training loss and 83.41% validation loss, as shown in Figure 4.

B. Testing Result

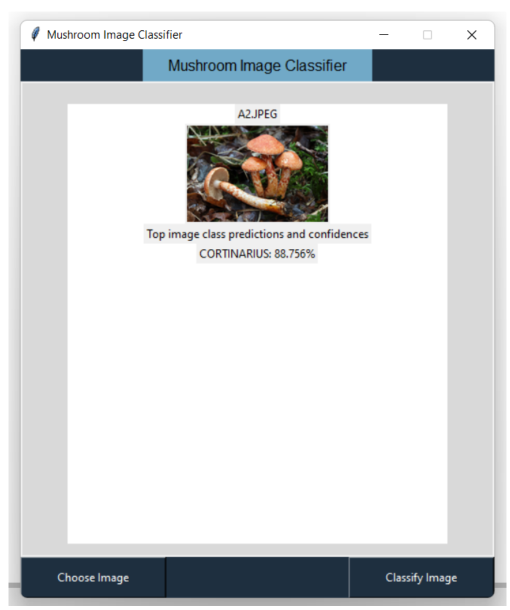

Figure 6. Model Testing

Figure 6 depicts the model being tested. The mushroom image being tested is part of the Cortinarius genus. The model predicts that the image is part of the Cortinarius genus with an 88.756% confidence score.

After testing the model on different pictures, the range of confidence score varies from 1% to 89%.

V. CONCLUSION & RECOMMENDATION

The system show a wide range of confidence score when it comes to classifying the mushroom images into their respective genus. Many factors have contributed to this. First, various mushroom species have similar appearances. Second, the model is not optimized and not trained to a larger dataset. Thus, resulting in the model having difficulties classifying mushroom images.

To future researchers, it is advised not to implement this system as is, but to consider the following changes. One, instead of classifying between mushroom genus, implement the model with known mushroom species such as (e.g. Shiitake, Matsutake, etc.). Two, classifying mushroom images into two classes: edible or poisonous.

VI. REFERENCES

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