MUSHROOM CLASSIFICATION USING DEEP LEARNING

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled **"MUSHROOM CLASSIFICATION USING DEEP LEARNING"**, submitted by **ABUL KALAM LOTIF** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **15-07-2024.**

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We hereby declare that this project has been done by us under the supervision of **Mr. Amir Sohel (ARS), Lecturer, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma. [Font-12, Font Color- Black, Alignment-Justify]

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Finally, we must acknowledge with due respect the constant support and patience of our parents.

ABSTRACT

As a useful and diverse part of ecosystems, mushrooms are important in many areas, such as the gastronomic, medicinal, and environmental. To classify 6000 photos of mushrooms from various species, this study uses deep learning techniques. The principal aim is to create a reliable and precise model that can distinguish between various types of mushrooms, thereby advancing the field of mycology and facilitating applications linked to mushrooms. The collection of photos includes pictures of several types of mushrooms, such as Reishi, oyster, pink oyster, golden oyster, button, and blue oyster mushrooms, among others. A complete and well-balanced dataset for training and assessment is provided by the 1000 photos that each class represents. Resizing, contrast stretching, and gamma correction are some of the augmentation techniques used to improve the dataset by creating variances in the photos. Cutting-edge deep learning models like ResNet50, MobileNetV2, VGG16, and VGG19 are used and optimized for the classification task. Using transfer learning, the classification performance for mushroom photos is optimized by utilizing the information obtained from pre-trained models on big datasets. The project intends to address particular issues related to the variety of mushroom forms, colors, and attributes in addition to achieving high classification accuracy. The goal of the research is to determine the best architecture for tasks involving the classification of mushrooms through a comprehensive process of experimentation and comparison analysis of several models. To further emphasize the model's practical relevance, the proposed work also includes an evaluation of the model using real-world mushroom datasets. Metrics including accuracy, precision, recall, and F1 score will be used to analyze the classification findings. Potential uses of the proposed model in forestry, environmental monitoring, and agriculture are also covered in the study.

Keywords: Handwritten image classification, deep learning, 5-layer CNN, VGG16, MobileNetV2, VGG19, ResNet50.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

Scientists and environment lovers alike find mushrooms to be intriguing organisms that exhibit a vast variety of shapes, sizes, and colors. These fungi are incredibly diverse, ranging from the little button mushrooms we find in our grocery stores to the enormous shiitake mushrooms valued in Asian cuisine. To further add to their intricacy and mystery, mushrooms can be found in a variety of settings, including meadows and woods. Imagine a woodland floor that is carpeted in colorful mushrooms, each one having a distinct look. While some mushrooms have complicated gills or pores beneath, others have smooth crowns resembling umbrellas. Their colors range from vivid reds to deep blues, and they can be as big as a dinner plate or as small as a pebble. [1]

Traditionally, the knowledge of mycologists—scientists who study fungi—has been essential to the identification of mushrooms. However, new techniques for mushroom identification and categorization have surfaced as a result of technological advancements, particularly in the fields of artificial intelligence and computer vision. Researchers may teach computers to identify patterns and characteristics that tell one mushroom species apart from another by training computer algorithms on massive datasets of photos of mushrooms. The identification procedure might be streamlined and made more widely available with the help of this automated method. [2]

In this research, we work on 7 various classes of mushrooms. We set out to investigate the field of mushroom categorization with state-of-the-art deep learning methods. We will make use of advanced models like ResNet50, VGG16, VGG19, MobileNetV2 and our specially created convolutional neural network (CNN). Our goal is to accurately train these models to classify different species of mushrooms by providing them with a diverse collection of photos taken in different settings. Our objective is to aid in the creation of trustworthy and effective instruments for the identification of mushrooms, which will assist the mycological, ecological, and agricultural domains. We want to improve our knowledge of mushrooms and their place in the natural world through our work. We also developed a mobile application that can detect mushroom classes.[3]

1.2 Background and Present State

Background:

As symbionts, food and medicine sources, and decomposers, mushrooms are a diverse group of fungi that are essential to ecosystems. However, because there are so many kinds of mushrooms and their physical distinctions are frequently slight, accurately identifying them is a difficult undertaking. Historically, the identification of mushrooms has been dependent on the knowledge of mycologists and the utilization of field guides, both of which can be laborious and prone to mistakes.

The development of automated systems for mushroom categorization has gained increasing attention since the introduction of digital imagery and the progress made in artificial intelligence, especially in the area of deep learning. A subset of machine learning methods called deep learning models has demonstrated astounding performance in a variety of domains when it comes to image identification jobs. These models are excellent for the task of classifying mushrooms because they can extract intricate patterns and features from big datasets.

Present State:

Several research has investigated the application of deep learning to the categorization of mushrooms in recent years, utilizing different convolutional neural network (CNN) architectures to attain high accuracy rates. The following essential elements are involved in the current status of deep learning-based mushroom classification.

1. Data Collection: A wide range of sources, including online databases, field research, and community contributions, are used to compile enormous datasets of photos of mushrooms. Typically, these files contain photos of mushrooms in various species, habitats, and states.
2. Reprocessing: To boost model performance, images are subjected to preprocessing techniques including scaling, contrast enhancement, gamma correction, and data augmentation. The development of strong models requires increasing the diversity of training data and standardizing the images, which these processes help to achieve.
3. Model Selection: For the categorization of mushrooms, several deep learning architectures are used, including VGG16, VGG19, MobileNetV2, ResNet50, and InceptionV3. Metrics including accuracy, precision, recall, and F1-score are used to assess the performance of these models, which vary in terms of their strengths

and complexities.

4. Training and Evaluation: Models are tested on different validation and testing sets (20% for testing, 10% for validation) and trained on a sizable amount of the dataset (usually 70%). Every model's performance is evaluated, and the top-performing models are determined.
5. Applications: The trained models are employed in a number of applications, such as real-time applications for identifying mushrooms, tools for mycologists, and public education materials. The goal of these applications is to improve the efficiency, accuracy, and accessibility of mushroom identification.

We have successfully used these methods in our study to use five distinct deep-learning models to categorize seven different kinds of mushrooms. According to your findings, InceptionV3 was the most accurate, followed by ResNet50, MobileNetV2, VGG16, and VGG19. This work shows that deep learning has the potential to increase accuracy and efficiency in the field of automated mushroom classification, and it makes a valuable contribution to the ongoing efforts in this direction.

Scientists and environment lovers alike find mushrooms to be intriguing organisms that exhibit a vast variety of shapes, sizes, and colors. These fungi are incredibly diverse, ranging from the little button mushrooms we find in our grocery stores to the enormous shiitake mushrooms valued in Asian cuisine. To further add to their intricacy and mystery, mushrooms can be found in a variety of settings, including meadows and woods. Imagine a woodland floor that is carpeted in colorful mushrooms, each one having a distinct look. While some mushrooms have complicated gills or pores beneath, others have smooth crowns resembling umbrellas. Their colors range from vivid reds to deep blues, and they can be as big as a dinner plate or as small as a pebble.

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In this research, we work on 7 various classes of mushrooms. We set out to investigate the field of mushroom categorization with state-of-the-art deep learning methods. We will make use of advanced models like ResNet50, VGG16, VGG19, MobileNetV2 and our specially created convolutional neural network (CNN). Our goal is to accurately train these models to classify different species of mushrooms by providing them with a diverse collection of photos taken in different settings. Our objective is to aid in the creation of trustworthy and effective instruments for the identification of mushrooms, which will assist the mycological, ecological, and agricultural domains. We want to improve our knowledge of mushrooms and their place in the natural world through our work. We also developed a mobile application that can detect mushroom classes.

1.3 Problem Statement

The primary difficulty in classifying mushrooms is differentiating between edible species and those that are dangerous, as well as correctly identifying particular varieties within these divisions. The wide variety of forms, hues, and textures that many mushroom species display complicates this work and makes it challenging to develop an all-encompassing set of categorization guidelines.

1.4 Objectives

The purpose of this research article is to investigate how well several deep learning algorithms—such as MobileNetV2, VGG16, VGG19, ResNet50, and InceptionV3—classify mushrooms from photographs. Our goal is to create a reliable and effective system for classifying mushrooms by utilizing deep learning. This approach may help both novice and experienced mushroom enthusiasts confidently distinguish between various species.

1.5 Scope and Limitations

The endeavor to classify mushrooms has several limits, even with the encouraging outcomes. The model's generalizability is hampered by the dataset's low diversity, which only covers Seven mushroom classes and may not include environmental variation. Performance is further impacted by problems with image quality and the constraints of data augmentation. Overfitting is a concern associated with complex models like VGG19 and ResNet50, and the high processing power needed for training may be a barrier. Because user-generated data can vary and field conditions can fluctuate, real-world application is yet questionable. The potential for misclassification, particularly with regard to dangerous mushrooms, raises ethical questions and highlights the importance of precision and dependability. Other problems include accessibility and usefulness for non-experts. To keep the model accurate, updates must be made often, necessitating constant data collecting and retraining. A balanced dataset is required for equal performance because bias in the training data can result in unfair classifications. It will take further investigation, better model designs, and substantial real-world validation to overcome these constraints.

1.6 Report Organization

The structure of this research study is as follows:

Introduction: An overview of the study, problem statement, motivation, goals, project scope, project outcome, and report organization are given in the introduction.

Literature Review: Examines the body of research on deep learning methods, applicable methodology, and mushroom classification.

Methodology: Outlines the model architecture, training process, assessment measures, data collecting and preprocessing strategies, and deep learning algorithms that were employed.

Results: Describes the performance analysis and experimental findings for various deep learning models used in the classification of mushrooms.

Discussion: Examine the data, talk about the significance of the findings, and identify possible areas for development.

Conclusion: Provides an overview of the main research and makes recommendations for future directions.

1.7 Summary

In conclusion, this study examines the use of deep learning algorithms in the classification of mushrooms. With the use of CNN architectures like InceptionV3, VGG16, VGG19, ResNet50, and MobileNetV2, our goal is to create an automated system that can correctly identify different species of mushrooms from visual data. The results of this study could advance our knowledge of how to classify mushrooms scientifically as well as lead to the creation of useful resources for both novices and professionals.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

My research involves investigating the classification of mushrooms through the use of multiple deep learning models, such as MobileNetV2, VGG16, VGG19, ResNet50, and a customized CNN algorithm. These models are used to examine and group mushrooms according to their characteristics. The objective is to improve efficiency and accuracy in the classification of mushrooms by applying cutting-edge deep-learning techniques. An overview of the chosen models and their uses in the classification of mushrooms is given in this study of the literature. My work focuses on classifying mushrooms using deep learning models such as MobileNetV2, VGG16, VGG19, ResNet50, and a customized CNN algorithm. The objective is to increase mushroom identification accuracy by utilizing cutting-edge deep learning algorithms. The selected models and their applicability to the categorization of mushrooms are summed up in this literature review.

2.2 Related Works

Yağmur DEMİREL et al. (2021) show in their research to categorize mushrooms in their natural environment, a deep learning strategy is proposed in this work. The goal of the study is to determine the best approach for classifying mushroom photos generated by popular CNN models. They gathered information from data that an I Naturalist professional had labeled. The model called "Mobilenetv2_GAP_flatten_fc" is employed in this investigation. When categorizing using the validation data, the model demonstrates 97.20% accuracy. [4]

Lia Farokhah et al. show in their research showing Mushrooms are one food that may be easily found in nature. Eight existing designs are recommended to be modified by this study: Modified DenseNet201, DenseNet121, VGG16, VGG19, ResNet50, InceptionNetV3, MobileNet, and EfficientNet B1. Classification and hyperparameter learning were the domains in which this architecture was developed. The comparison results show that the MobileNet design has the lowest computing performance and the highest accuracy when compared to the other eight architectures. An accuracy of 82.7% is obtained when the confusion matrix is used for evaluation. Due to its reduced pre-processing and lower computation architecture, Modified MobileNet operates at fastest speed. [5]

In their research, Norbert Kiss et al. show the effectiveness of a cutting-edge general classification network; as a result, we selected EfficientNet as a scalable model to meet our needs for memory and processing power. Due to hardware resource limitations, they are utilizing a particular neural network in their research. Similar to CNN, Mobilenetv2, and VGG16, our data set of 106 species is used for performance evaluation, with the top method achieving 92.6% accuracy in this study. [6]

K.B.A.Bhagyani Chathurika et al. Present a CNN image processing strategy that separates edible mushroom species from other types of mushrooms, identifies edible mushrooms using artificial neural networks, and uses CNN image processing techniques to determine the growth stage of edible mushrooms. They suggest analyzing photos of mushrooms and differentiating between edible mushroom species using image processing techniques like feature extraction, segmentation, and classification. They used a dataset that they trained in their research to achieve 90% accuracy for their project. Their ultimate accuracy is 90% and they primarily concentrate on the ANN Algorithm. [7]

Y.D Surige et al. demonstrate in their research how to use ICT to prevent inefficiencies in the mushroom-farming process. The technique is designed with "Oyster Mushrooms," one of the most common varieties of mushrooms, in mind. Four features are provided by the system to ensure accurate mushroom growth. The system offers four features to guarantee precise mushroom growth. Four features are provided by the system to ensure accurate mushroom growth. The system is connected to the farmer via a mobile application. It can monitor environmental factors with an accuracy of 89% and detect harvest time with an accuracy of 92%. The disease detection and control recommendation function is based on the support of CNN with a mobile Net V2 model, and the yield prediction function is developed using the support of Long Short-Term Memory (LSTM). Additionally, the system has a 99% accuracy rate in detecting diseases related to mushrooms and a 97% accuracy rate in predicting the monthly yield of mushrooms grown.[8]
Jiacheng Rong, Pengbo Wang, et al. demonstrate and suggest an oyster-mushroom harvesting robot that is capable of carrying out harvesting tasks throughout the greenhouse. The sensing module and the end-effector are the two most important parts of the harvesting robot. Field tests demonstrate the viability and resilience of the suggested robot system; in these tests, the success rate for identifying mushrooms is 95%, the success rate for harvesting mushrooms is 86.8% (excluding damage to the mushrooms), and the harvesting time for a single mushroom is 8.85 seconds. [9]

Tanmay Sarkar1 et al. In this work, a quality prediction model based on artificial intelligence was built for oyster mushroom samples. In terms of anticipated Hedonic number, which is regarded as one of the most trustworthy scales of raw fruit quality evaluation characteristics, the suggested model tends to predict the samples' gradually declining quality. An artificial neural network is used in the suggested strategy to create the estimator. The scheme's high prediction accuracy and ease of analysis enable basic sample screening without the need for a panel of experts to make the same difficult decisions. This task is particularly challenging in the context of the current pandemic. [10]

Peng Wang et al. In their study, they built Bilinear Convolutional Neural Networks (B-CNNs) with a transfer learning-based attention mechanism model to classify Amanita. After the model is trained, the network parameters are updated using the Adam optimizer, and pre-training is carried out using the weight on ImageNet. The findings demonstrate that our model achieves excellent accuracy (95.2%) and good generalization ability while significantly reducing the number of parameters when compared to previous models. In regions with low computing resources, this effective classification approach offers a new option for classifying mushrooms.[11]

Xiu-Ping Li et al. The purpose of this work is to forecast the total polyphenol content of four porcini mushrooms and to create a method for quick and reliable species recognition utilizing Fourier transform mid-infrared (FT-MIR) spectroscopy and data fusion techniques. There is a strong correlation between FT-MIR and total polyphenol content, which could be used to estimate the approximate polyphenol content of mushrooms, according to the correlation coefficient and residual predictive deviation of the best prediction model, which were 86.76% and 2.40%, respectively. [12]

Wan Adibah Wan Mahari et al.demonstrate the value-added recovery of the waste mushroom substrate (WMS), a plentiful waste in the mushroom cultivation industry, and the manners, conditions, and state of research related to the cultivation and valorization of oyster mushroom species and waste generated in mushroom cultivation. While the use of WMS as an energy feedstock could result in cleaner bioenergy sources than conventional fuels, the use of WMS as biofertilizer has demonstrated satisfactory performance when compared to standard chemical fertilizer. [13]

Shuhaida Ismail et al. shows in this study the behavior of mushrooms, including their smell, population, and habitat, as well as their form, surface, and color in the cap, gills, and stem. As the Using the Decision Tree (DT) technique, the Principal Component Analysis (PCA) algorithm is utilized to pick the optimal features for the classification experiment. On a typical

Mushroom dataset, measurements were made on the classification accuracy, the coefficient metric, and the building time of a classification model. The most highly ranked component that contributes to the high classification accuracy was determined to be the behavioral characteristic of "odour." The dataset contained 22 number of nominal attributes (features). The statistics from the dataset showed that the edible mushroom has 4,208 absolute count with 0.518%, while the poisonous mushroom has 3,916 absolute count with 0.482% . [14]

Julian White et al. In their Study Based on important clinical characteristics that are useful in differentiating distinct poisoning illnesses, they suggest six main groupings. Numerous cases of mushroom poisoning share certain clinical characteristics, most notably gastrointestinal symptoms. Group 1: Poisoning from poisonous mushrooms. syndromes with a particular main disease of internal organs, When compared to earlier models, the results show that their model achieves outstanding accuracy (94.2%) and good generalization ability with a substantially smaller number of parameters. [15]

Kemal TUTUNCU et al. The UC Irvine Machine Learning Repository's Mushroom dataset was the one utilized in this investigation. Considering 22 characteristics in the Using the mushroom dataset and four distinct machine learning methods, models have been developed to distinguish between toxic and edible mushrooms. The Naive Bayes, Decision Tree, Support Vector Machine, and AdaBoost algorithms yielded 90.99%, 98.82%, 99.98%, and 100% classification success rates for these models, respectively. Based on an analysis of this data and the physical characteristics of the mushrooms, the AdaBoost model was able to detect 100% of the time whether the mushrooms were toxic or edible. [16]

Agung Wibowo et al. they Using mining data as one of the methods to extract computer code, a learning machine can quickly classify if a mushroom is toxic or not. supported understanding. The top three data mining classification methods are now compared as follows: Decision Treee (C4.5), Naïve Bayes, and Support Vector Machine (SVM). The research methodology employed is an experiment using a WEKA-assisted tool that has been tested in an algorithmic comparison of the three. The Agaricus and Lepiota mushroom data are utilized in the testing process. The UCI machine learning repository's The Audubon Society Field Guide to North American Mushrooms provided the mushroom data. The testing's findings show that the C4.5 algorithm and the SVM are equally accurate by 96.4%. [17]

Norbert Kiss et al. The objective of this work is to solve a classification problem for mushrooms by methodically addressing the aforementioned important questions. We first describe how we assembled and prepared an appropriate training data set, and then we explain why we chose a particular neural network in light of hardware limitations. We discuss various training options, including task-specific subnetworks, gradual freezing, model size changes, incremental-size learning, and transfer learning. Our data-set of 106 species is used to evaluate performance, with the best method achieving 92.6% accuracy. [18]

2.3 Comparison between existing works

Table 2.3.1 Comparative analysis with previous work

Authors	Dataset	Proposed Model	Accuracy
Yağmur DEMİREL [1]	5470 image Data set	Mobilenetv2_GAP_flatten_fc	97.20%
Lia Farokhah [2]	643 Raw image data set	MobileNetv3	82.7%
Norbert Kiss [3]	400 images Raw Data	VGG16	92.6%
K.B.A.Bhagyani Chathurika [4]	4200 raw image dataset	ANN Algorithm	90%
Xiu-Ping L i [9]	650 image dataset	Fourier transform mid-infrared (FT-MIR)	86.76%

2.4 Open Issues

A review of the literature finds several important additions to the body of knowledge on research about mushrooms. However, there exist certain gaps that warrant further exploration and investigation. First off, while several studies concentrate on the taxonomy of different species of mushrooms, a more thorough examination of the identification and taxonomy of a wider variety of mushrooms is required. The existing body of research primarily focuses on popular kinds, such as Amanita and oysters, which leaves a gap in our understanding of less common or regionally distinctive mushrooms.

Second, for mushroom classification, most of the examined works use conventional convolutional neural network (CNN) architectures including MobileNet, VGG, and ResNet. The area of deficiency is the investigation of more recent structures and sophisticated methods that could improve precision and effectiveness. To improve classification results, for example, attention processes, transfer learning, or ensemble models could be added.

Moreover, although a few research discuss the application of AI to growth-related or mushroom quality prediction, comprehensive predictive models that take into account a wider range of quality variables are lacking. There is a need for models that use intelligence analysis to forecast a variety of attributes, including taste, nutritional value, and therapeutic qualities. Furthermore, the majority of current research focuses on the taxonomy of mushroom species, ignoring other general elements of mushroom farming such as culture, disease detection, and robotic harvesting. Comprehensive studies that integrate technology solutions for automated harvesting, disease detection, and cultivation monitoring and cover the full lifecycle of mushroom farming are lacking.

2.5 Summary

The review of the literature dives into deep-learning models for mushroom classification, using ResNet50, MobileNetV2, VGG16, VGG19, and a bespoke CNN algorithm. The principal aim is to improve mushroom identification accuracy by utilizing cutting-edge deep-learning methodologies. An overview of the selected models and their importance in the classification of mushrooms is given in this section.

CHAPTER 3
METHODOLOGY

3.1 Overview

The goal of this research is to create a deep learning framework for species identification of mushrooms. To classify mushroom photos taken in the field, the suggested approach would combine a bespoke CNN architecture with pre-trained convolutional neural networks (CNNs) such as MobileNetV2, VGG16, VGG19, and ResNet50. For training and evaluation, the study makes use of a sizable collection of photos of mushrooms taken in the field.

3.2 Proposed Methodology

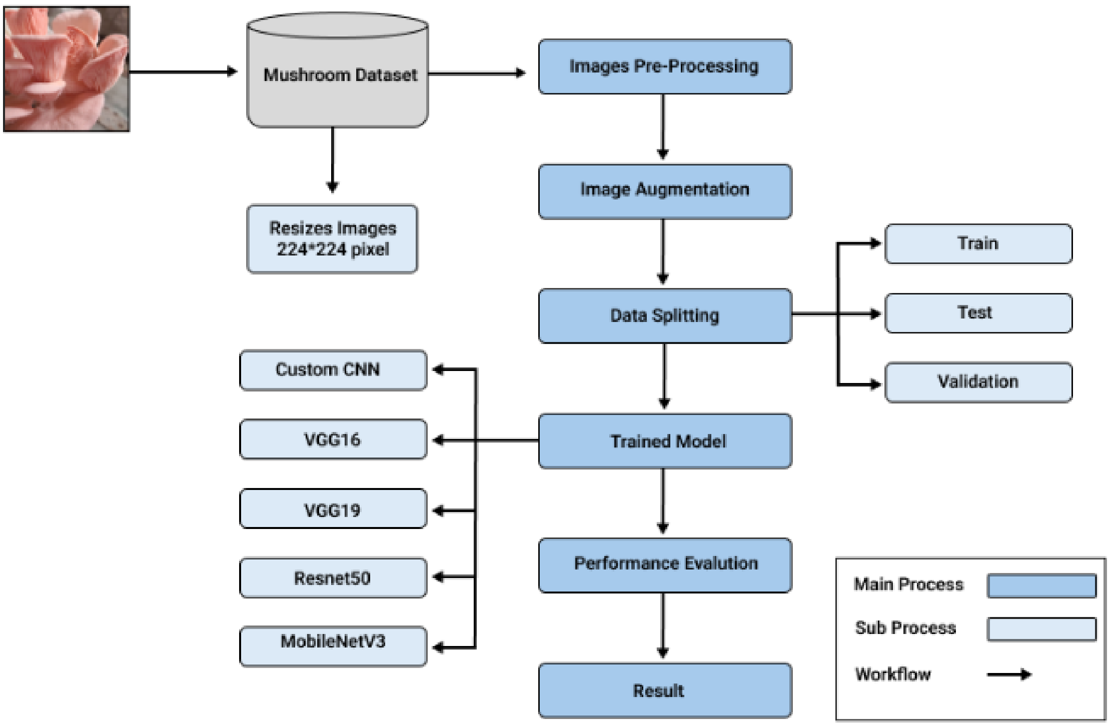

Figure: 3.2.1 Methodology

The goal of this research is to create a deep learning framework for species identification of mushrooms. To classify mushroom photos taken in the field, the suggested approach would combine a bespoke CNN architecture with pre-trained convolutional neural networks (CNNs) such as MobileNetV2, VGG16, VGG19, InceptionV3, and ResNet50. For training and evaluation, the study makes use of a sizable collection of photos of mushrooms taken in the field

field. I will follow these steps for the deep learning framework for mushroom species identification:

3.2.1 Data Collection:

We collect data from Mushroom Savar Mushroom Centers, Mushroom Development Institute, Bismah Mushroom Agro and BD Mushroom. We have been there so many days to collect mushroom images. We go there every morning. Some mushrooms are not available there. So we had to buy some mushrooms. Blue Oyster Mushroom is only available in winter. We collect this mushroom from the mushroom center's AC room. We used our phone camera to capture the mushroom image. We used the Samsung S20, Google Pixel 5 phone's camera. There are seven various classes of mushrooms. We captured a total of 2800 images of seven various classes of mushrooms. We take 400 images of each class of mushroom.

3.2.2 Dataset Description:

The dataset used in this study includes a large collection of photos of mushrooms that were taken in the field. Seven different kinds of mushrooms are carefully chosen to exhibit diversity within the dataset, each of which contributes special qualities. The following provides a thorough analysis of the species of mushrooms included in the dataset:

Reishi Mushroom: Reishi mushrooms, or Ganoderma lucidum, are well-known for their therapeutic qualities and glossy appearance. The collection offers insights into the growth patterns of Reishi mushrooms by containing photos that show the fungus at different phases of development.

Oyster Mushroom: The Pleurotus genus, popularly referred to as oyster mushrooms, is highly valued for its culinary applications. The dataset includes a variety of oyster mushroom specimens that exhibit differences in size, color, and appearance.

Pink Oyster Mushroom: Pleurotus diamond, often known as the Pink oyster mushroom, is a species that adds vivid and unique color to the dataset. Pictures display the distinctive pink coloring at various stages of development.

Golden Oyster Mushroom: Pleurotus citrinopileatus, also known as the Golden Oyster mushroom, is distinguished by its delicate flavor and bright yellow color. Images that highlight the special qualities of the Golden Oyster mushroom are included in the dataset.

Button Mushroom: The Button mushroom, or Agaricus bisporus, is a commonly farmed plant distinguished by its traditional white appearance. The dataset's images illustrate several stages of growth, which helps to explain the morphological variances in the data.

Mushroom, contributes to the dataset's unique blue color, hence enhancing its diversity. The pictures show this mushroom's distinct traits during different stages of its existence. Each image in the carefully annotated dataset has a label that corresponds to the appropriate species of mushroom. The foundation for training and assessing machine learning models is this extensive and thoroughly documented dataset, which guarantees the models' efficacy in identifying and categorizing these many kinds of mushrooms.

Phoenix Oyster Mushrooms: Popular edible mushrooms like the Phoenix Oyster Mushroom are grown for their delicate flavor and simplicity of production. It usually has an oyster- or fan-shaped whitish cap that varies in color from white to light brown. In woodlands, these mushrooms are frequently observed growing on decaying wood, particularly on hardwoods. Their delicate texture and mildly sweet flavor make them highly prized in the culinary arts. Phoenix oyster mushrooms are valued for their nutritional qualities as well because they're an excellent source of fiber, protein, and vitamins and minerals. Additionally, because of their capacity to decompose contaminants and organic debris, they are employed in a variety of ecological applications, including bioremediation.

Blue Oyster Mushroom

Button Mushroom

Golden Oyster Mushroom

   

Oyster Phoenix Oyster Pink Oyster Reishi

Figure 3.2.2 Simple Datasets

3.2.3 Image Pre-Processing:

Resizing:

Resizing entails bringing the picture proportions to a uniform size. In my instance, I downsized the pictures to 224 by 224 pixels. For consistency in training and classification, this standardization makes sure that every image given into the deep learning models has the same size.

Figure 3.2.3.1 Image

Figure 3.2.3.2 Resizing Image

Contrast Stretching:

Expanding the range of intensity values in an image is a method called contrast stretching, which improves contrast. I improved the overall contrast and enhanced the distinguishability of the details in the image by applying a contrast stretching factor of 1.3, which increased the difference between the brightest and darkest pixels in the image.

Figure 3.2.3.3 After contrast Stretching Figure 3.2.3.4 Before Contrast Stretching

Gamma Correction:

Gamma correction is a nonlinear adjustment made to an image's intensity values. I adjusted the image's brightness and contrast using a gamma correction factor of 1.2 to make it more in line with human perception. This change may help make features in the image's bright and dark areas easier to see. [19]

Figure 3.2.3.5 Image Figure 3.2.3.6 Gamma Correction Image

3.2.4 Image Augmentation:

By transforming the original photos in different ways, augmentation creates new training data. In my instance, I increased the number of photos in each class from 400 to 1200 in order to expand the dataset. Flipping, rotating, translating, scaling, and adding noise are a few examples of augmentation techniques. I can give the deep learning models additional varied instances to learn from by augmenting the dataset, which can help them become more accurate in classifying and generalizing previously unseen mushroom photos.

Table 3.2.2.1: Augmentation Table

Class	Before Augmentation	After Augmentation	Augmentation Image
Blue Oyster Mushroom	400	1200	
Button Mushroom	400	1200	
Golden Oyster Mushroom	400	1200	
Oyster Mushroom	400	1200	
Phoenix Oyster Mushroom	400	1200	
Pink Oyster Mushroom	400	1200	
Reishi Mushroom	400	1200	
Total	2800	8400	

3.2.4 Data verification:

Structural Similarity Index (SSIM): The similarity between the original mushroom photographs and the images produced or categorized by your deep learning models (MobileNetV2, VGG16, VGG19, ResNet50, and your customized CNN algorithm) may be evaluated using SSIM. A high SSIM score validates the classification process' accuracy because it shows that the outcomes of the classification closely match the original images in terms of structure, contrast, and brightness.

Peak Signal-to-Noise Ratio (PSNR): PSNR can be used to assess how well my models' categorization results are produced. I am able to test each model's amount of information preservation and fidelity quantitatively by comparing the PSNR values between the original mushroom photos and the categorized images. Greater image quality and detail preservation during the categorization process is indicated by higher PSNR values.

Root Mean Squared Error (RMSE): The RMSE metric is utilized to measure the variations that occur between the initial photographs of mushrooms and the categorized images generated by your deep learning models. Reduced root mean square error (RMSE) values indicate higher classification accuracy and closer resemblance to the original images, confirming my models' efficacy in correctly recognizing and categorizing mushrooms.

Learned Perceptual Image Patch Similarity (LPIPS): The visual resemblance between the original mushroom photos and the categorized images produced by my models can be evaluated using LPIPS. I can assess how well the categorization results capture the high-level perceptual properties of the mushrooms by comparing the LPIPS scores. Reduced LPIPS scores signify increased perceptual similarity, which validates my models' ability to accurately capture and maintain significant visual attributes during the classification process. [20]

Table 3.2.3.1: Data verification

Sample	Class	MSE	RMSE	PSNR	SSIM
	Blue Oyster Mushroom	104.11	10.20	27.96 dB	0.6811
	Button Mushroom	101.73	10.09	28.06 dB	0.1933
	Golden Oyster Mushroom	103.21	10.16	27.99 dB	0.3115
	Oyster Mushroom	103.57	10.18	27.98 dB	0.1831

	Phoenix Oyster Mushroom	107.57	10.38	27.81 dB	0.1962
	Pink Oyster Mushroom	107.63	10.37	27.81 dB	0.2676
	Reishi Mushroom	107.96	10.39	27.80 dB	0.2497

3.2.5 Data Splitting:

I have 8400 data for model running. Here I keep 70% data for training, 20% data testing and 10% data for validation. [21]

3.3 Hardware/Software Requirement

Computer with High Performance:

Processor: A minimum of an AMD Ryzen 7 or Intel Core i7, preferably with several cores for parallel processing.

Memory (RAM): 32GB or more is advised for handling huge datasets and lengthy training procedures, however, a minimum of 16GB is required.

Graphics Processing Unit (GPU): A top-tier NVIDIA GPU with CUDA capability, such as the RTX 2080, RTX 3080, or better. GPUs are essential for speeding up the deep learning model training process.

Capacity: To accommodate the dataset, model weights, and other relevant files, an SSD with at least 1TB of capacity is required. Training procedures and data loading are accelerated by fast storage.

Cooling System: Effective cooling system to control the heat produced by extended GPU.

Software Requirement

1. Operating System: - Windows 10/11, macOS, or a Linux distribution (such as Ubuntu). Because Linux offers superior support for a wider range of deep learning frameworks and tools, it is frequently chosen for deep learning.

2. Programming Languages: - Python: The main language used to put deep learning models into practice. Make sure you have installed Python 3.6 or later.

3. Frameworks for Deep Learning:

TensorFlow: A well-liked deep learning framework that can be used for deep learning model deployment and training.

Keras: A high-level neural network API that runs on top of TensorFlow and makes deep learning model development and training easier.

PyTorch: A different deep learning framework that is popular in research and quite versatile.

4.Library and Tool Section:

For performing numerical operations on matrices and arrays, use NumPy.

Pandas: For analysis and data processing.

OpenCV: For image manipulation operations like augmentation and scaling.

Matplotlib/Seaborn: For graphing outcomes and data visualization.

scikit-learn: For more metrics and machine learning tools.

Libraries for Image Augmentation: These include albumentations and imgaug for data augmentation.

5. The IDE (Integrated Development Environment):

- Jupyter Notebook: For testing and interactive development.
- PyCharm or VS Code: For managing and developing code.

6. CUDA Toolkit: Required in order to take use of GPU acceleration on NVIDIA GPUs. Ascertain that the appropriate versions of CUDA and DNN are installed in accordance with TensorFlow or PyTorch's version requirements.

7. Version Control: - Git: For teamwork and version control. platforms for hosting repositories, such as GitLab or GitHub.

8. Virtual Environment: - To manage dependencies and guarantee reproducibility, construct isolated environments using tools like virtualenv or conda.

Deep learning models for mushroom classification may be developed, trained, and implemented in a stable environment thanks to this hardware and software combination.

3.4 Project Management and financial Analysis

We intend to develop a website and include the model in it so that anybody may share a photograph and receive an estimate of a skin lesion. We first require a small amount of funding to develop a website, integrate it with the model, and store that information.

Development Expenses:

Table 3.4.1: Project Management and financial Analysis

SN	Components	Estimated Cost (BDT)
01	Development of a Website	11,000
02	servers and hosting	8,000
03	SSL certificate and domain name	6000
04	Administrative and Legal	5000
05	**Total operational and incidental costs**	3000

3.5 Summary

This study suggests a deep learning-based approach to identify different kinds of mushrooms from photos taken in the field. The work attempts to accomplish accurate classification and make a contribution to the field of mushroom identification by utilizing pre-trained and customized CNN models. Meeting the specified criteria for data.

CHAPTER 4
IMPLEMENTATION

4.1 Overview:

In this research, we used a dataset of 8,400 photos (1,200 images each class) to categorize images of mushrooms into seven different classes. To assess how well various cutting-edge convolutional neural network (CNN) designs performed on this challenge, we put them into practice. InceptionV3, MobileNetV2, ResNet50, VGG16, and VGG19 were the architectures used.

4.2 Train Model/Prototype Design

I perform a thorough comparison analysis of the Model Prototyping. Before finalizing the model architectures and training processes, several prototypes were developed to experiment with different CNN architectures and their configurations. The prototyping phase included:

1. Model Selection: The initial selection of pre-trained models included InceptionV3, MobileNetV2, ResNet50, VGG19, and VGG16, all of which are well-known for their performance in image classification tasks.
2. Layer Customization: For each selected model, the top layers were replaced with custom layers to adapt the models to the 7-class mushroom classification task. The custom layers typically included a Global Average Pooling layer followed by a Dense layer with 512 units and ReLU activation, and a final Dense layer with softmax activation for the 7 output classes.
3. Hyperparameter Tuning: Various hyperparameters such as learning rate, batch size, and the number of epochs were experimented with to find the optimal settings for each model. This was done using grid search and manual tuning based on the validation performance.
4. Early Stopping and Checkpointing: Early stopping was implemented to monitor the validation loss and stop training when the performance plateaued, thus preventing overfitting. Model checkpoints were saved to retain the best model weights during training.

4.3 System Testing/ Model Evaluation

Model evaluation is a critical part of the machine learning pipeline to ensure the model's performance is robust, reliable, and generalizable to new data. For this project, the evaluation was conducted using several metrics and methods on the test dataset.

To evaluate the models' performance, we used the following metrics:

1. **Accuracy**: The primary metric used to evaluate the models. It is the ratio of correctly predicted instances to the total instances.
2. **Confusion Matrix**: Provides insight into the true positive, true negative, false positive, and false negative predictions, giving a detailed breakdown of the classification performance.
3. **Precision, Recall, and F1-Score**: These metrics were computed for each class to evaluate the models' performance more comprehensively:

Model description:

VGG16 and VGG19: These are two very deep convolutional neural network architectures developed by the Visual Geometry Group at the University of Oxford. They were among the first models to demonstrate the benefits of using very deep networks for image classification tasks. VGG16 and VGG19 consist of 16 and 19 weight layers respectively, with multiple convolutional layers followed by fully connected layers. They are known for their uniform architecture with small 3x3 convolutional filters and max-pooling layers.[22]

Layer Architecture:

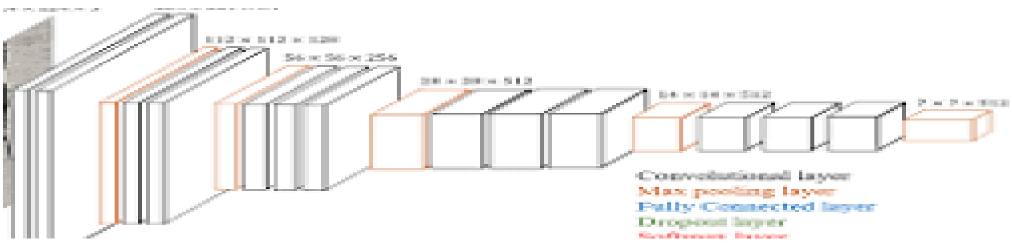

Figure: 4.3.1 VGG-16

Layer Architecture:

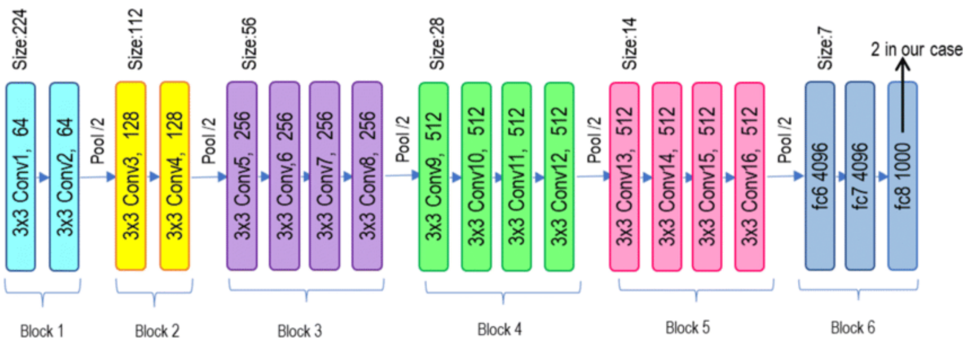

Figure: 4.3.2 VGG19

ResNet50: ResNet (Residual Network) is a deep residual learning framework that introduced skip connections to alleviate the vanishing gradient problem in very deep neural networks. ResNet50 is a 50-layer residual network that won the ImageNet competition in 2015. It uses residual blocks that allow the network to effectively learn residual mappings, enabling much deeper architectures to be trained successfully.[23]

Layer Architecture:

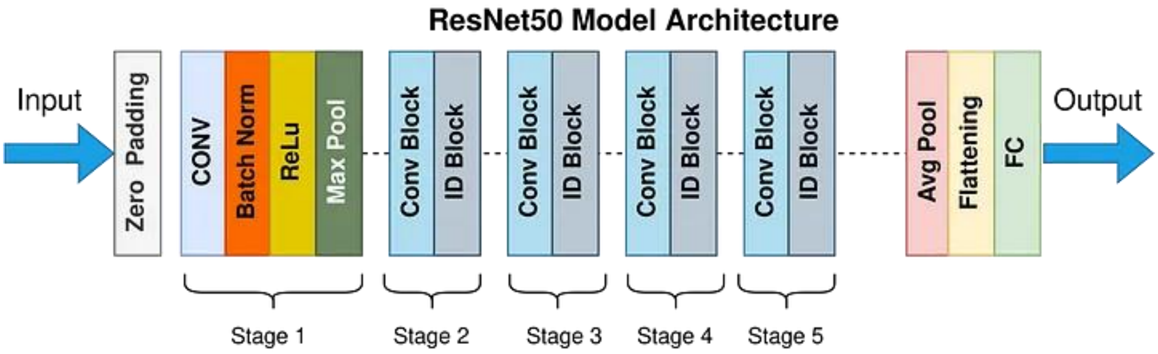

Figure: 4.3.3 ResNet50

MobileNetV2: MobileNetV2 is a more recent convolutional neural network architecture

designed for mobile and embedded vision applications. It builds upon the previous MobileNetV2 model but introduces new efficient building blocks and advanced neural architecture search techniques. MobileNetV2 aims to strike a balance between high performance and low computational cost, making it suitable for deployment on resource-constrained devices like smartphones or IoT devices.[24]

Layer Architecture:

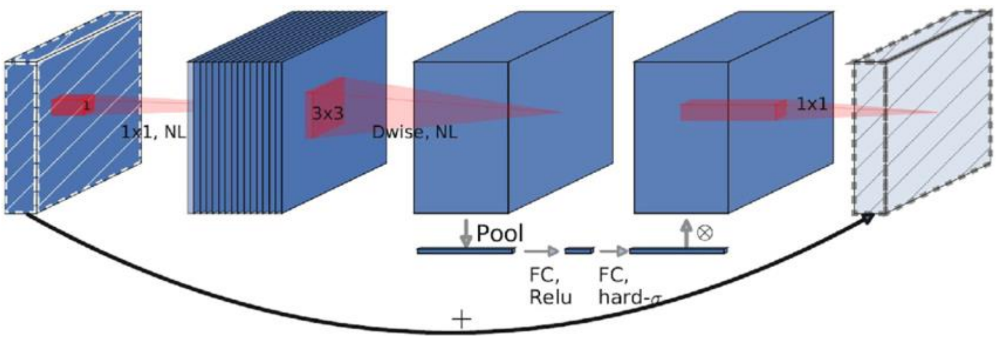

Figure: 4.3.4 MobileNetV2

InceptionV3

A deep convolutional neural network architecture renowned for its effectiveness and precision in image categorization is the InceptionV3 model. Initial convolution and pooling layers are used to minimize spatial dimensions. Multiple Inception modules are then used to capture distinct features using parallel convolutions with variable filter sizes. Efficiency and dimensionality reduction are further enhanced with factorized convolutions and reduction modules. The last layers consist of a fully linked softmax layer for classification and global average pooling to help with training. With more than 23 million parameters, its architecture strikes a good compromise between efficiency and complexity, which makes it appropriate for jobs like classifying mushrooms.

Layer Architecture:

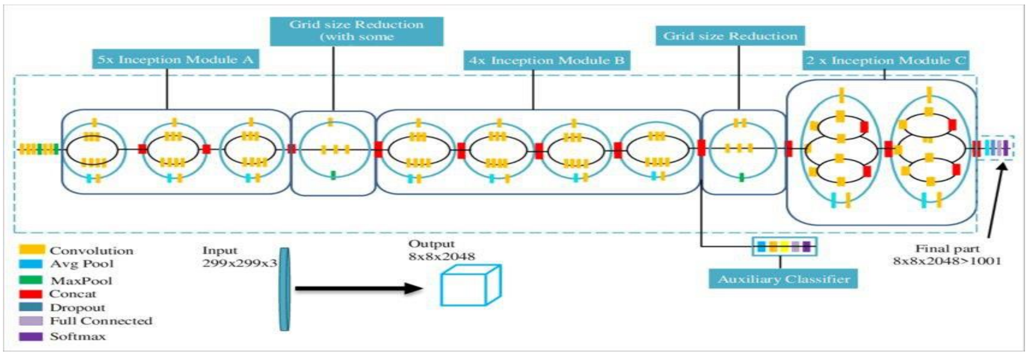

Figure: 4.3.5 InceptionV3

4.4 Summary

In this project, we explored the application of deep learning models for the classification of mushrooms into 7 distinct classes. The dataset consisted of 1200 images per class, which were divided into training (80%), validation (10%), and testing (10%) sets. Five pre-trained Convolutional Neural Network (CNN) models were selected for this task: InceptionV3, MobileNetV2, ResNet50, VGG19, and VGG16.

The implementation involved several critical steps, including data augmentation to enhance generalization, fine-tuning the pre-trained models by replacing their top layers, and extensive hyperparameter tuning to optimize performance. Early stopping and model checkpointing were employed to prevent overfitting and to save the best-performing model configurations.

The evaluation of the models on the test dataset yielded the following accuracies:

Table 4.4.1. Accuracy for Classification of Individual CNN Networks in Detecting

Model	Training Accuracy	Model Accuracy

InceptionV3	0.91%	91%
MobileNetV2	0.898%	89%
ResNet50	0.54%	54%
VGG19	0.85%	85%
VGG16	0.877%	87%

Among these models, InceptionV3 and MobileNetV2 demonstrated the highest accuracy, making them the most suitable for the mushroom classification task. VGG19 and VGG16 also performed well, but ResNet50 showed significantly lower accuracy, indicating it was less effective for this specific dataset.

In conclusion, the project successfully identified InceptionV3 and MobileNetV2 as the most efficient models for mushroom classification, highlighting the importance of model selection and fine-tuning in achieving high accuracy in image classification tasks. This work provides a foundation for further research and potential applications in automated mushroom identification systems.

CHAPTER 5
RESULT AND ANALYSISS

5.1 Overview

This study using deep learning algorithms to classify seven different various of mushrooms. Blue oyster mushrooms, button mushrooms, golden oyster mushrooms, oyster mushrooms, phoenix oyster mushrooms, pink oyster mushrooms, and reishi mushrooms were among the mushrooms used in this investigation. 8400 photos in total were employed, with 20% (1680 images) going toward testing, 70% (5880 images) going toward training, and 10% (840 images) going toward validation. The effectiveness of five distinct deep learning models MobileNetV2, ResNet50, InceptionV3, VGG16, and VGG19 was assessed in relation to this classification task. The ResNet50 model performed poorly on the dataset despite many optimization attempts, underscoring the necessity of cautious model selection and tuning in deep learning applications.

5.2 Experimental/Simulation Result

In this paper, we conducted trials on mushroom classification using a dataset of 8400 pictures that represented seven different mushroom classes: Blue Oyster Mushroom, Button Mushroom, Golden Oyster Mushroom, Oyster Mushroom, Phoenix Oyster Mushroom, Pink Oyster Mushroom, and Reishi Mushroom. The dataset was partitioned using 10% (840 images) for validation, 20% (1680 images) for testing, and 70% (5880 images) for training. We employed five deep learning models: VGG16, VGG19, MobileNetV2, ResNet50, and InceptionV3 to evaluate each model's performance in classifying the mushroom pictures. The following displays the thorough results of our investigation along with the accuracy percentages that each model was able to achieve:
VGG16: This model had an 87% accuracy rate. This model, which is well known for its depth and simplicity demonstrated strong feature extraction abilities by successfully distinguishing between the various mushroom classes.

In this paper, I employed five different pre-trained Convolutional Neural Network (CNN) architectures for this project: InceptionV3, MobileNetV2, ResNet50, VGG19, and VGG16. These models were chosen for their proven effectiveness in image classification tasks. Each model was fine-tuned on our mushroom dataset to achieve optimal performance

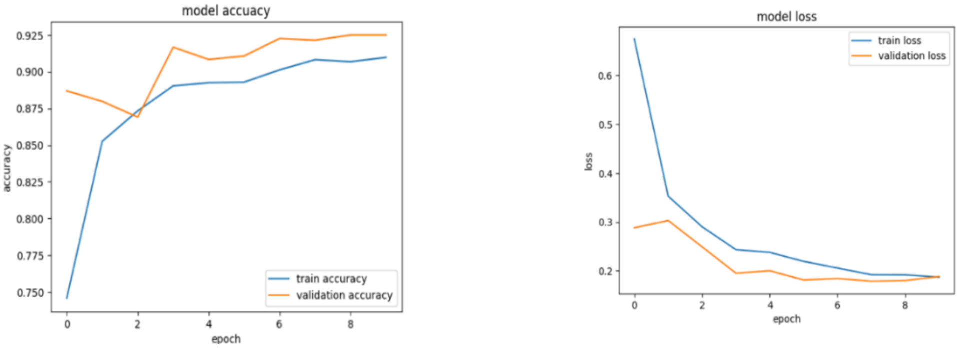

Figure: 5.2.1 InceptionV3 Training-Validation Loss and Accuracy.

InceptionV3 is a deep CNN architecture that uses factorized convolutions and aggressive regularization to achieve high performance. It was pre-trained on the ImageNet dataset and fine-tuned on our mushroom dataset. The model achieved an accuracy of 91%.

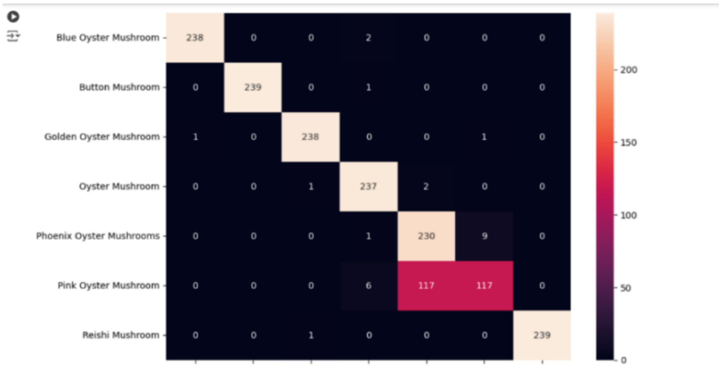

Figure: 5.2.2. Confusion Matrix of Proposed InseptionV3.

MobileNetV2 is designed for mobile and edge devices. It uses depthwise separable convolutions to reduce the number of parameters and computational cost. The model, pre-trained on ImageNet and fine-tuned on our dataset, achieved an accuracy of 89%.

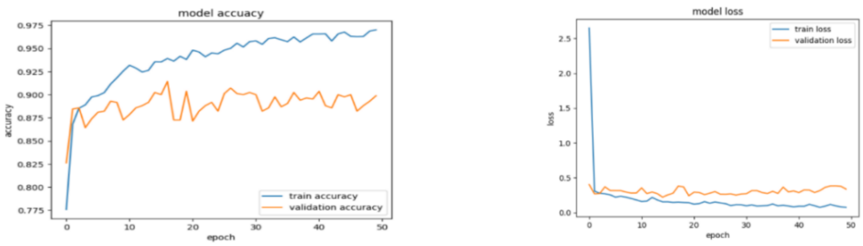

Figure: 5.2.3 MobileNetV2 Model Training-Validation Loss and Accuracy.

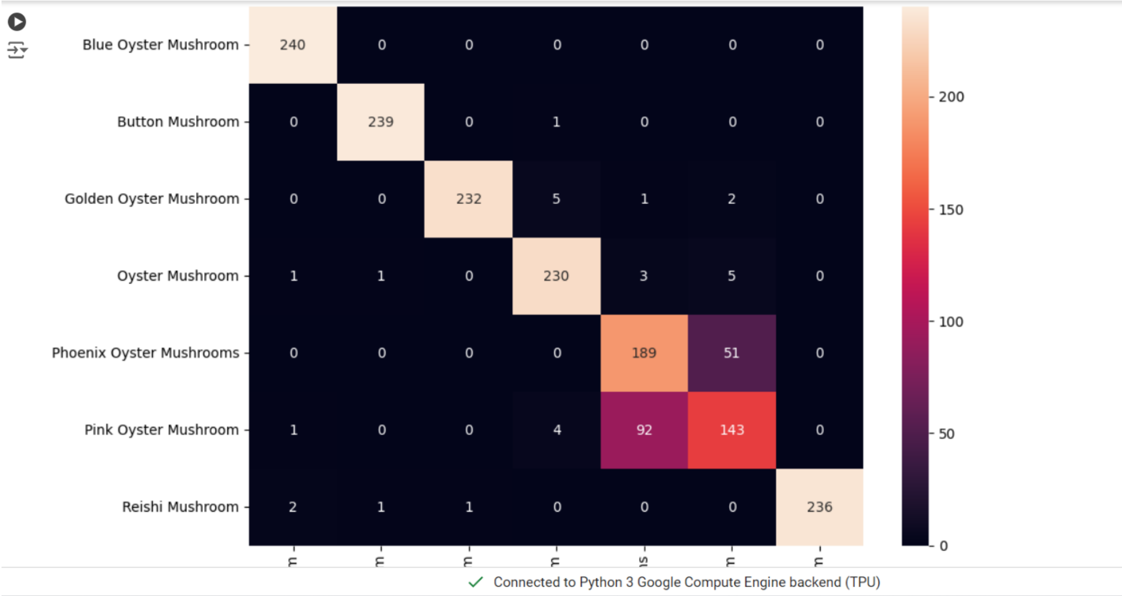

Figure 5.2.4: Confusion Matrix MobileNetV2.

ResNet50 introduces residual learning, enabling the training of deeper networks by mitigating the vanishing gradient problem. Despite its robust architecture, the ResNet50 model underperformed in our project, achieving an accuracy of 53%. This could be attributed to the specific characteristics of our dataset or insufficient fine-tuning

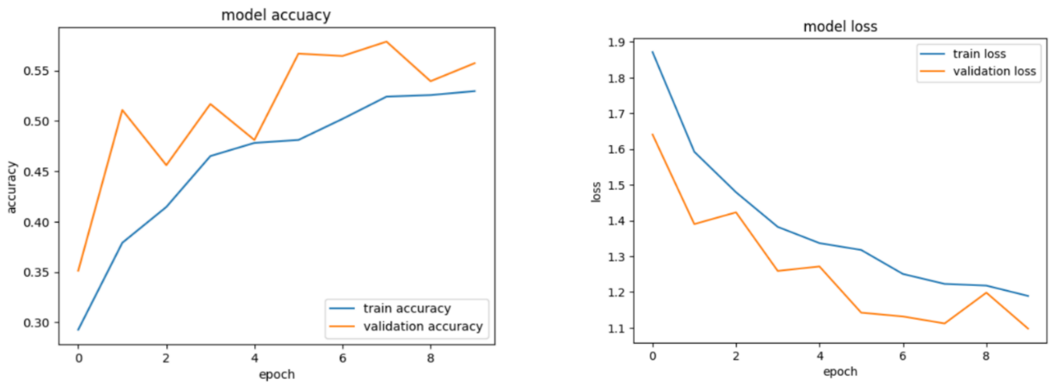

Figure 5.2.5: Resnet50 Model Training-Validation Loss and Accuracy.

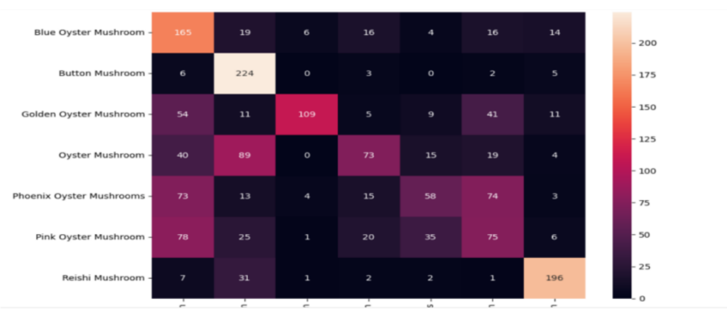

Figure 5.2.6: Confusion Matrix Resnet50.

VGG19 is a deeper version of the VGG network, with 19 layers. Known for its simplicity and effectiveness, VGG19 was fine-tuned on our mushroom dataset and achieved an accuracy of 87%

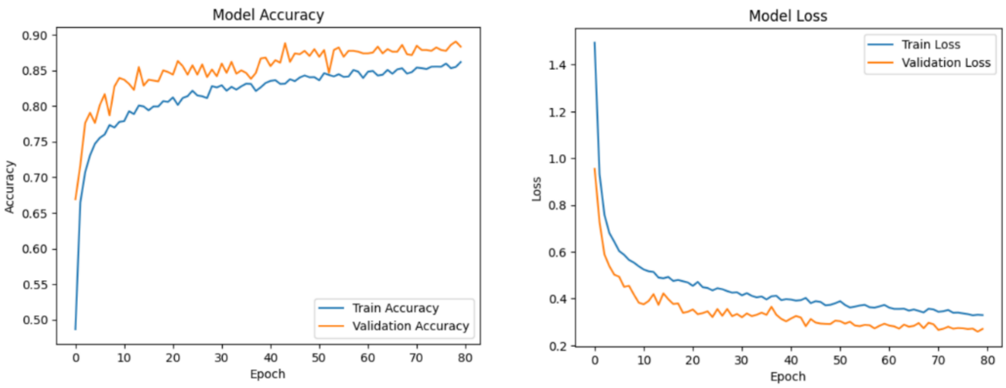

Figure 5.2.7: VGG19 Model Training-Validation Loss and Accuracy

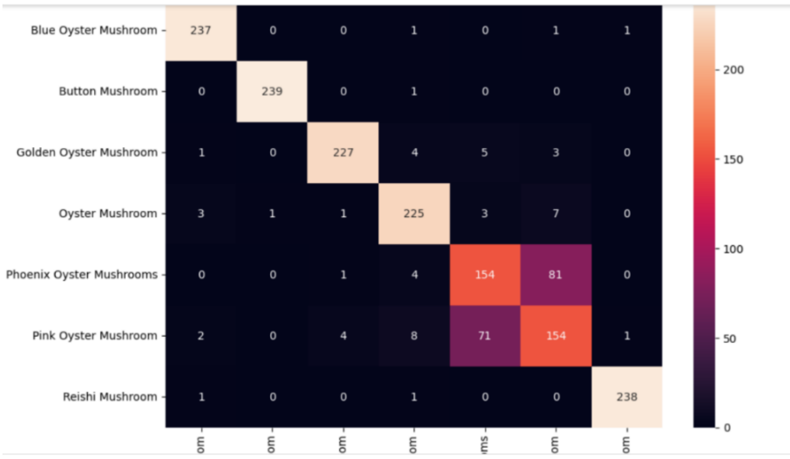

Figure 5,2.8: Confusion Matrix of VGG19

VGG16, another member of the VGG family, is slightly shallower than VGG19, with 16 layers. This model was also fine-tuned on our dataset and achieved an accuracy of 84%.

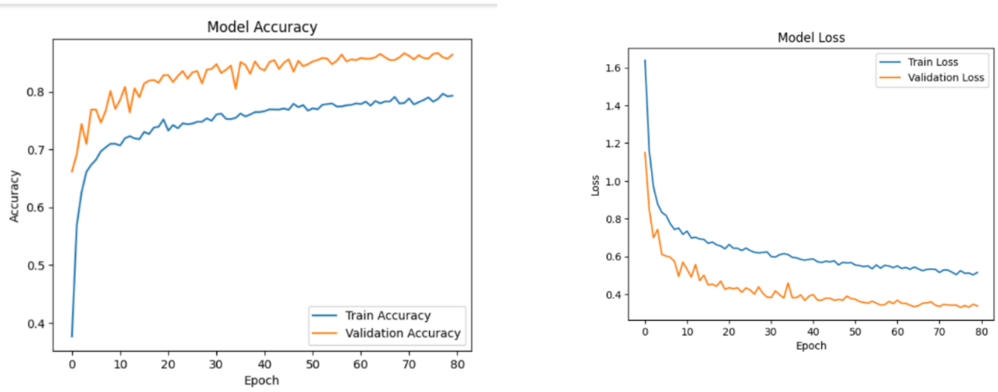

Figure 5.2.9: VGG16 Training-Validation Loss and Accuracy

Comparing model accuracies is essential to comprehending the trade-offs between performance and complexity. Though deeper architectures such as VGG19, MobileNetV2, and ResNet50 demonstrated more accuracy, factors like processing efficiency and practicality in the real world started to matter more. Further research into transfer learning, computational effectiveness, and the models' capacity to generalize to a variety of signature styles was guided by these subtleties. The ultimate objective is still to create a signature verification system that is superior in terms of accuracy, usefulness, and flexibility. InceptionV3 achieved the highest accuracy rate of 91%. Because of its complex architecture, which includes multiple convolutional filter sizes, this model did remarkably well in capturing a range of features across the different mushroom classes. The high accuracy rate demonstrates how well the system can categorize and extrapolate from the mushroom photographs.

5.3 Performance/ Comparative Analysis

The models' performance varied significantly, as shown by a comparison analysis:

VGG16 vs. VGG19: Both models showed good performance, with VGG16 just managing to surpass VGG19. The extra layers in VGG19 might have led to overfitting but did not significantly improve accuracy.

MobileNetV2: This model is among the best because of its efficiency and design, which enabled it to attain an accuracy of 89%. Its lightweight architecture is very useful for deploying in settings with limited resources.

ResNet50: ResNet50 is a strong model but did not do well with this dataset. Its accuracy of 54% was far lower than that of the other models, indicating that, in the absence of additional changes, its depth and complexity would not be appropriate for this classification job. With an accuracy rate of 91%, InceptionV3 is the best-performing model. Its architecture works well for classifying mushrooms since it can capture various characteristics and performs well.

Web Application

Flask(__name__) initializes the Flask application. After loading the TensorFlow Lite model, the interpreter is used to extract the model's input and output details.both interpreter and get_input_details().obtain_output_details(), preparing the model for forecasting.

The predict_image method uses interpreter.invoke() to do inference after preprocessing the image and setting it as the input tensor for the TensorFlow Lite interpreter. It obtains the output tensor and uses the index of the maximum value to determine the anticipated class. After that, a predetermined list of mushroom types is mapped to this index.

Web interface management is done by the upload_image route. It renders the index.html template without a picture or prediction on a GET request. It looks for an uploaded file on a POST request, saves it, uses predict_image to predict the class, and then renders the uploaded image and prediction into the index.html template.

GET request: Renders index.html without prediction or picture. Using a POST request, the file is found, saved, and then shown with the image and prediction in index.html. Predict_image is then used to forecast the class. Call the app and verify that __name__ == "__main__" to run in debug mode.Run with "debug=True" to enable automatic server reloads and comprehensive error messages. Put the code in app.py, make index.html in a templates directory, and put model.tflite in the same directory.

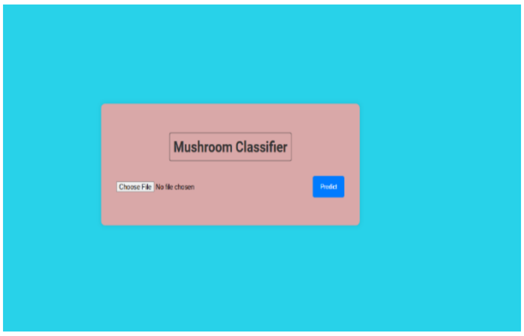

Figure 5.3.1: Web Page Image

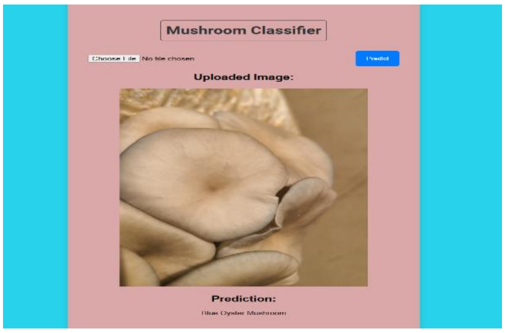

Figure 5.3.2: Mushroom classifier Image

5.4 Summary:

This study showed that deep learning models are useful for classifying various kinds of mushrooms. With an accuracy of 91%, InceptionV3 outperformed the other five models in the evaluation, with MobileNetV2 coming in second at 89%. Additionally performing well were VGG16 and VGG19, with accuracies of 87% and 86%, respectively. Despite several optimization attempts, ResNet50 did not match the dataset well, obtaining a substantially lower accuracy of 54%. These results underline the fact that not all architectures are appropriate for every dataset, highlighting the significance of model selection and tuning in deep learning applications. To further improve classification performance and application, future study could examine further model alterations, bigger and more varied datasets, and real-world validation.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT & SUSTAINABILITY

6.1 Impact on Life:

The benefits of precise mushroom categorization with deep learning algorithms are manifold across multiple domains. These models enhance public health and safety by limiting the intake of toxic mushrooms, hence lowering the incidence of mushroom poisoning. Economically speaking, they increase market expansion for edible mushroom species and agricultural output. In terms of education, they are useful resources for community involvement and mycological education, which promotes a heightened understanding and respect for biodiversity. Technologically, they enable people to make educated decisions by advancing AI applications and making complex tools accessible to non-experts. In terms of the environment, these models encourage sustainable foraging methods and aid in attempts to conserve biodiversity, upholding ecological equilibrium. Deep learning's overall impact on health, education, technology, and the environment is significant, improving people's quality of life and encouraging sustainable resource management. This is especially true for the classification of mushrooms.

6.2 Impact on Society & Environment

The application of deep learning to successfully classify mushrooms has important social ramifications. Identifying mushrooms accurately has significant advantages in a number of areas, including public health, food safety, and agriculture.

Agriculture: By using these models, growers may better identify edible mushrooms and improve mushroom production techniques, producing higher-quality and more abundant harvests.

Food Safety: These models can aid in the prevention of potentially fatal mushroom poisoning occurrences by reliably differentiating between edible and deadly species. This is because it can be challenging to tell differentiate between similar-looking species.

Public health: By using these models to guarantee safe mushroom ingestion and the safe extraction of the nutritional benefits of mushrooms, health experts and foragers can lower the danger of mushroom poisoning.

Education: These models can be used as teaching aids for mycology classes, raising public understanding of the variety and significance of mushrooms for human health and ecosystems. There may be environmental advantages to the use of deep learning in the classification of mushrooms.

Biodiversity Conservation: Accurate identification can support the study and documentation of the biodiversity of mushrooms, assisting conservationists in keeping an eye on and safeguarding threatened species.

Ecological Research: By using these models, scientists can better understand fungal involvement in nutrient cycling and the functions of various mushrooms in diverse environments.

Sustainable Foraging: These models support sustainable foraging methods that don't deplete local mushroom populations by assisting foragers in differentiating between edible and non-edible mushrooms.

6.3 Ethical Aspects

The use of deep learning algorithms for classifying mushrooms raises a number of ethical questions.

Accuracy and Safety: Ensuring the models' accuracy is crucial because if dangerous mushrooms are mistakenly recognized as edible, there could be grave health hazards. The models must be updated and validated on a regular basis in order to remain reliable.

Accessibility: It's critical to make these technologies available to a large audience, especially people living in rural and impoverished areas. Allowing everyone to use these models can democratize the advantages of technology.

Bias and Fairness: To prevent any biases that could impair the model's performance across various mushroom species and environmental circumstances, it is crucial to make sure the training dataset is extensive and diverse.

6.4 Sustainability Plan

The following tactics can be used to guarantee the mushroom categorization project's long-term viability and sustainability:

Perpetual Enhancement: Consistently incorporating fresh information and cutting-edge methodologies into the models to preserve exceptional precision and adjust to novel situations.

Community Engagement: Gathering large and varied datasets through community participation in data collecting and validation procedures will increase the robustness and dependability of the model.

Partnerships: Working together to promote the application and advantages of the technology with agricultural organizations, academic institutions, and environmental groups.

Training and Support: Ensuring safe and responsible use by offering users the tools and training they need to make the most of the models and recognize their limitations. Financing and Resources: obtaining continuous funds and resources to assist with the technology's development, research, and adoption.

The application of deep learning models to the classification of mushrooms raises significant ethical questions while providing significant benefits to society and the environment. A comprehensive sustainability strategy is necessary to optimize these advantages and guarantee the technology is used fairly and ethically.

6.5 Summary

Sustainability, life, society, and the environment are all significantly impacted by the use of deep learning algorithms for mushroom categorization. These methods provide significant advantages by raising agricultural output, promoting community and educational involvement, and increasing public health and safety. They support biodiversity conservation and encourage environmentally sound behaviors. A thorough sustainability strategy with ongoing updates, teamwork, and ethical considerations will guarantee this technology's long-term viability and beneficial effects. All things considered, the project shows how AI may be used to solve problems in the real world, enhance quality of life, and encourage the wise and sustainable use of natural resources.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

This study has shown that deep learning models are effective in classifying seven different species of mushrooms, including blue, button, golden, oyster, phlox, pink, and reishi mushrooms. Five distinct deep learning models—VGG16, VGG19, MobileNetV2, ResNet50, and InceptionV3—were trained and assessed using a dataset of 8400 pictures. According to the experimental data, InceptionV3 had the highest accuracy rate (91%), followed by ResNet50 at 54%, MobileNetV2 at 89%, VGG16 at 87%, and VGG19 at 85%. These results highlight how deep learning methods can improve the precision and effectiveness of mushroom categorization, which can have important ramifications for agriculture, public health, and biodiversity preservation.

7.2 Further Suggested Works

This work could be expanded upon in a number of ways by future research:

1. Increase Dataset Diversity: More species of mushrooms and environmental factors can be included to improve the generalizability and robustness of the model.
2. Enhance Model Architectures: Investigating more complex or hybrid deep learning architectures may help to increase the efficiency and accuracy of classification.
3. Real-World Application: By creating and evaluating mobile applications for real-time mushroom recognition, this technology may become more widely available.
4. Multi-Modal Approaches: A more thorough categorization system might be produced by combining image data with additional data types, such as geographic or environmental data.
5. Community Involvement: Gathering a variety of datasets and enhancing model performance can be accomplished by including the public in data gathering and validation activities.

7.3 Limitations

There are a few restrictions on this study, even with the encouraging outcomes. The applicability of the model to different mushroom species and environmental conditions may be limited due to the limited diversity of the dataset. Real-world diversity cannot be adequately captured by variations in image quality or by relying solely on data augmentation. VGG19 and ResNet50 are examples of complex models that run the danger of overfitting, and their training takes a lot of processing power. Potential misclassifications give rise to ethical considerations, particularly with regard to toxic mushrooms, highlighting the importance of accuracy and dependability. Other problems include accessibility and usefulness for non-experts. To keep the model accurate, updates must be made often, necessitating constant data collecting and retraining.

To protect the integrity of the research, any potential conflicts of interest, such as biases in the training data or ties to groups that might profit from the study's findings, should be openly declared and handled. It will take constant research, better model designs, and substantial real-world validation to overcome these constraints.

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Appendix

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: MUSHROOM CLASSIFICATION USING DEEP LEARNING

Student ID: 203-15-3897

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a **pneumonia detection** problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**

CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing of COs, Knowledge Profile (K), and Attainment of Complex Engineering Problems (EP):

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (With Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project uses various CNN architectures, deep neural networks, and data augmentation approaches to perform image processing and classification tasks, thereby demonstrating **fundamental engineering (K3) principles**. By using cutting-edge CNN architectures including InceptionV3 MobileNetV2 Resnet50, VGG16, and VGG19 to improve mushroom picture categorization, the project showcases specialized **knowledge (K4).**	**Page no:** [15-22] Section: [3.2] Page no: [1] Section: [1.1]
				My project requires the integration of different classes and I have designed a Mobile application that covers K5 and K6.	**Page no:** [15-22] **Section:** [3.2] **Page no:** [24-25] **Section:** [3.4]
				Through the synthesis of insights from recent	**Page no:** [7-12] **Section:**

				studies, this study ensures **K8** and advances Mushroom Image Classification through deep learning, demonstrating a thorough comprehension of current approaches.	[2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in Mushroom Image Classification, including limitations of traditional methods and the complexities of integrating transfer learning and deep CNNs. Through comparative analysis, it confronts challenges in understanding spatial distributions, offering insights for refining diagnostic methodologies.	**Page no:** [13-14] **Section:** [2.4, 2.5]

3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP-3** by meticulously comparing experimental outcomes, highlighting Transfer Learning as the chosen significant solution for enhancing Mushroom Image Classification amidst multiple potential approaches.	**Page no:** [26] **Section:** [4.2]
4.	**EP4: Familiarity of Issues**	Yes	CO8	This project I have to research a lot of topics that I don't know much about to comprehend and analyze depression and mental health for my project. To be more precise, I need to figure out how to gauge depression.	Page no: [7-14] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A

7.	**EP7: Interdependence**	Yes	CO5	The complete strategy of this project offers a holistic solution to complicated obstacles in medical diagnostics, ensuring **EP-7.** It does this by combining numerous components across data collecting, statistical analysis, and proposed methodology. This approach tackles high-level problems.	**Page no:** [15-25] **Section:** [3.2, 3.3, 3.4]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project leverages a range of advanced resources including high-performance computing systems, GPUs, sophisticated deep learning frameworks, annotated datasets, and ethical data management practices to conduct systematic research and drive progress in mushroom classification using transfer learning and deep CNNs.	**Page no:** [25] **Section:** [3.5]
2.	**EA2: Level of interaction**	No			N/A
3.	**EA3: Innovation**	No		N/A	N/A

4.	**EA4: Consequences for society and the environment**	Yes		N/A	**Page no**: [31-36] **Section:** [5.1, 5.2, 5.4]
5.	**EA-5: Familiarity**	Yes		This project has societal benefits by enhancing the precision and speed of mushroom identification, aiding food safety, medical research, and environmental conservation. It also aligns with sustainable practices by using efficient computational resources and maintaining ethical standards in data usage.	**Page no**: [7,12-13] **Section:** [2.1, 2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	We have prepared a budget to evaluate and estimate the cost required for our FYDP.	**Page no**: 24-25
2	CO9	Yes	N/A	N/A
3	CO10	No	N/A	N/A

4	CO12	Yes	The project's focus on continuous learning (CO12) and adaptation within the evolving technological landscape is evident in its extensive data collection, rigorous statistical analysis, careful methodology development, and detailed experimental results. This commitment to ongoing improvement ensures we remain at the forefront of addressing current challenges.	**Page no:** 15-26 **Section:** [3.2, 3.3, 3.4, 3.5, 4.2]

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