

# Edible and Poisonous Mushroom Classification using Deep Learning

Akshaya KS<sup>1</sup> and Sanooja Beegam<sup>2</sup>

<sup>1</sup>Student, Musaliar College of Engineering & Technology, Pathanamthitta, Kerala

<sup>2</sup>Assistant Professor, Musaliar College of Engineering & Technology, Pathanamthitta, Kerala

**Abstract:** Mushrooms are a diverse group of fungi that exhibit a wide range of morphological characteristics, making their identification and differentiation between edible and poisonous species a challenging task. Accurate classification of mushrooms is of utmost importance for foragers, mycologists, and the general public to ensure safety and prevent ingestion of toxic species. Deep learning techniques, specifically Convolutional Neural Networks (CNNs), have shown remarkable performance in image classification tasks. This abstract proposes the use of CNNs to develop a robust and efficient system for classifying edible and poisonous mushrooms based on their visual characteristics. In this method, the user uploads an image of a mushroom and then determine whether it is edible or poisonous.

**Keywords:** Mushroom, Species, CNNs, Fungi..

## I. INTRODUCTION

Mushrooms are a diverse group of fungi that play significant roles in various ecosystems and have been consumed by humans for centuries. However, the identification and differentiation of edible and poisonous mushroom species can be challenging, as many visually similar species can have drastically different toxicity levels. This has led to numerous cases of mushroom poisoning and highlights the need for accurate classification systems to ensure safety. The primary goal of this research is to explore the application of CNNs in mushroom classification, specifically targeting the differentiation of edible and poisonous mushrooms. By developing a CNN-based model, we aim to provide a reliable and automated solution that can assist mushroom foragers, mycologists, and the general public in making informed decisions about mushroom consumption.

## II. PROPOSED SYSTEM

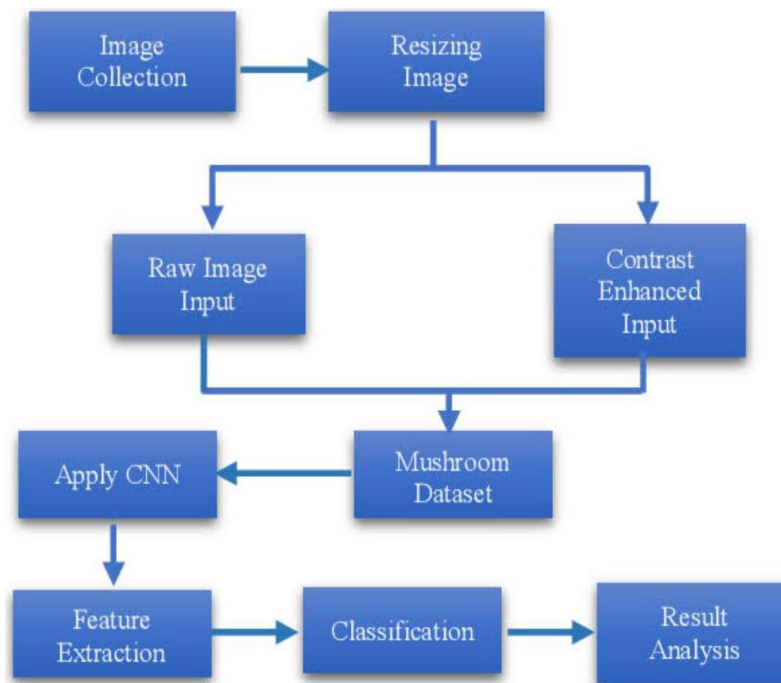
Goal is to use deep CNN to build an automated image categorization as edible or non-edible mushroom. CNN is currently at the state-of-the-art in image recognition. CNN includes categorization through learning; hence many images is required to do the experiment. The collected images must be pre-processed in order to produce a normalised image collection with the same size and shape as CNN expects pre-specified input sized images. Because the image is being uploaded, odour cannot be used to classify mushrooms. Through the convolution layer, the model is capable of extracting features important to the activation function required from the input image invisibly. The problem is viewed as a simple binary class, yielding two feature mining options: edible or non-edible.

## III. METHODOLOGY

- **Data Collection:** Collect a large dataset of mushroom images, including both edible and poisonous types. The images should be of high quality and captured from various angles and lighting conditions to increase the robustness of the CNN model.
- **Data Pre-processing:** Perform pre-processing steps on the dataset, such as resizing, normalization, and augmentation. The images should be resized to a uniform size, normalized to a standard scale, and augmented with transformations such as rotations, translations, and flips to increase the diversity of the dataset.
- **Split the Dataset:** Divide the dataset into training, validation, and testing sets. The training set is used to train the CNN model, the validation set is used to fine-tune the hyperparameters, and the testing set is used to evaluate the performance of the trained model.

- **Model Architecture:** Define the architecture of the CNN model. The model should consist of several convolutional layers with increasing depth and complexity, followed by a few fully connected layers.
- **Model Training:** Train the CNN model on the training dataset using an appropriate loss function and optimization algorithm. The loss function should be able to differentiate between edible and poisonous mushrooms. The optimization algorithm should minimize the loss function and improve the accuracy of the model.
- **Model Evaluation:** Evaluate the performance of the trained model on the testing dataset. The evaluation metrics can include accuracy, precision, recall, and F1 score. The model should also be evaluated on a new, unseen dataset to check for overfitting.
- **Model Deployment:** Deploy the trained CNN model to classify new mushroom images as edible or poisonous. The model can be integrated into a web or mobile application for easy access by users.

#### IV. SYSTEM ARCHITECTURE



Gather a dataset of mushroom images, ensuring that each image is labeled as "edible" or "poisonous." It's crucial to have a diverse and balanced dataset to achieve accurate classification results. Prepare the dataset for training by performing necessary pre-processing steps such as resizing the images to a uniform size, normalizing pixel values, and splitting the data into training and testing sets. When the image has good quality and brightness, it is used as a raw input. Contrast enhancement is a technique used to improve the visual quality and distinguishability of image details by increasing the contrast between different regions of an image. The raw input image and Contrast enhanced input image create a csv file of mushroom datasets. Train the CNN using the labeled mushroom images. During training, the CNN learns to extract relevant features from the images and make predictions based on them.

The CNN architecture utilizes convolutional layers to extract relevant image features and pooling layers to down sample the data. These features are then passed through fully connected layers for classification. During training, the CNN optimizes its internal parameters to minimize the classification error. Once trained, the model can be used to classify new mushroom images by feeding them into the network and obtaining a prediction of whether they are edible or poisonous based on the learned patterns. Overall, CNNs have proven to be effective in mushroom classification tasks by leveraging their ability to automatically learn and recognize visual features.

#### V. CONCLUSION

The suggested approach uses a CNN model to determine if mushrooms are edible or not. CNN's proposed algorithm outperforms others in mushroom classification. Along with this conclusion, the depth of the network and classification performance are not correlated and hence increasing complexity will not result in improved results. Improved deep learning models can be used to measure further accuracy gains. It is possible to investigate the ideal depth and size of filters.

#### VI. FUTURE SCOPE

As the amount of the training dataset grows, so does the performance of the developed model. In the future, we can integrate other qualities such as cap margins, cap size, stem colour, ecology, protein content, toxins, taste, and so on, as well as more records acquired as part of the research, and apply alternative machine learning techniques to the new dataset. As a result, the test model's accuracy will improve.

#### REFERENCES

- [1] N. Zahan, M. Z. Hasan, M. A. Malek and S. S. Reya, "A Deep Learning-Based Approach for Edible, Inedible and Poisonous Mushroom Classification," 2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD), 2021, pp. 440-444, doi: 10.1109/ICICT4SD50815.2021.9396845.
- [2] Al-Mejibli and D. Hamed Abd, "Mushroom Diagnosis Assistance System Based on Machine Learning by Using Mobile Devices Intisar Shadeed Al-Mejibli University of Information Technology and Communications Dhafar Hamed Abd Al-Maaref University College," vol. 9, no. 2, pp. 103-113, 2017. <https://doi.org/10.29304/jqcm.2017.9.2.319>
- [3] M. Alameady, "Classifying Poisonous and Edible Mushrooms in the Agaricus," International Journal of Engineering Sciences & Research Technology, vol. 6, no. 1, pp. 154-164, 2017.
- [4] Duong, L.T.; Nguyen, P.; Di Sipio, C.; Di Ruscio, D. Automated fruit recognition using Efficient Net and MixNet. Comput. Electron. Agric. 2020, 171, 105326.