Classification of Edible and Poisonous Mushrooms Using Machine Learning Algorithms

Mrs.D.S.L. Manikanteswari[1], Ms.Ch. Surya Kalyani[2]

[1]Assistant Professor, Department of CSE, Sri Vasavi Engineering College(A), Pedatadepalli, Tadepalligudem - 534101.
[2]M.Tech Student, Department of Computer Science, Sri Vasavi Engineering College(A), Pedatadepalli, Tadepalligudem -534101.

Abstract
There are millions of different types of mushrooms that grow all over the planet, but only one type is edible. Understanding how to differentiate between edible anddangerous mushrooms is an expertise that takes experience. Therefore, it's crucialto classify toxic and edible mushrooms. In addition to employing fungi's physical characteristics, machine learning (ML) techniques may be employed as well to distinguish between poisonous and edible mushrooms. Models will be developedto classify edible and deadly mushrooms based on features from the Mushroom collection and various distinct machine-learning algorithms. The results of this study were examined, and it was determined if the mushrooms were edible or dangerous by considering the physical characteristics of the mushrooms.

Keywords: Mushroom edibility, CNN Model, Healthy diet, poisonous mushrooms, Image Classification.

1. Introduction

As the fruiting bodies of fungi, mushrooms are a well-known dietary source. Some cultures and nations view different types of wild or field mushrooms as a delicacy. But a lot of mushrooms can be toxic when consumed, and the distinction between edible and poisonous mushrooms is not always an easy one. Not only that, but some supposedly “edible” mushrooms can be toxic when consumed by certain humans under certain conditions, which may be hard to predict. The number of people worldwide who die from eating mushrooms each year is unknown, it is at least 100 deaths per year, but Dadpour et al. consider that this number is a minimum estimate. In some countries, one of the types of fungal intoxication, intoxication by amatoxin with hepatocellular damage, becomes a noticeable burden on the healthcare system and, possibly, even one of the most common reasons for liver transplantation. Although there is no global information, local studies imply an increase in both the absolute number and the incidence of fungal intoxication.

The risk of fungal diseases in Europe is linked to large-scale migration, some of whom live in poor economic conditions and search for food. For this reason, poisonous mushrooms unknown to the immigrants were eaten. The toxicology of most fungal species is unknown, new toxins are constantly emerging, and known symptoms are reported outside their known natural ranges. Mushrooms are a highly diversified group of fungi that are ecologically important and have strong cultural connections with humans. Although many fungi are safe to eat and are favored for their culinary taste, some are toxic and deadly to ingest. Given the health hazards of eating poisonous mushrooms, it is critical to have a trustworthy automatic technique for determining which varieties are and are not edible. This automatically computed task is challenging because of the various complex features across and within species. Expert practitioners, in this case, mycologists, can generally accomplish this task visually by eye. Nevertheless, pattern classification in the feature space is challenging its visualization can lead to investigations in impossible areas.

2. Literature Survey

Automated Determination of Mushroom Edibility Using an Augmented Dataset

Author: S. Chamath.

This paper argues that the augmented database of mushroom features used here can successfully use color, texture, and three-dimensional measures to correctly classify edible and poisonous mushrooms thereby simultaneously increasing the accuracy and efficiency of classification using the same underlying methods and data. This paper investigates methods and databases employed to automatically measure the class of a mushroom as edible or poisonous in terms of species and observable features. Our research focuses on data-driven methods utilizing a large database of mushroom features. Results are comparative quantifications of the classification accuracy and efficiency.

Automatic Prediction of Poisonous Mushrooms by Connectionist Systems

Author: María Navarro-Caceres, María Angelica González Arrieta.

A brief overview of the classification system for edible and toxic mushrooms is provided in this study. In fact, there are not only classification systems but also applications that support expert decision-making. To achieve this goal, they studied different neural network models and learning algorithms and choose the best one based on the test outcomes.

Identification of Edible and Non-Edible Mushroom Through Convolution Neural Network

Author: Devika G, Asha Gowda Karegowda.

In this paper, they used image data of mushrooms and used machine learning algorithms such as sNet, L eNet, AlexNet, cNet, and DCNN to classify mushrooms as edible or inedible. Classification was perform ed and performance was evaluated using different CNN network architectures.

Machine Learning Methods to Classify Mushrooms for Edibility

Author: Rakesh Kumar Y, Dr. V. Chandrasekhar

A survey of the literature on the classification of poisonous and non-poisonous mushrooms is provided in this article. Learning approaches like Naïve Bayes, KNeural Networks, Support Vector Machine (SVM), Artificial Neural Network (ANN), and Decision Tree techniques have been employed on mushroom categorization. In this overview of the literature, the performance of all different mushroom classification methods, advantages, and disadvantages encountered in classifying mushrooms using machine learning techniques have been collected and compared.

Classification of Mushroom Fungi Using Machine Learning Techniques

Author: Ottom, Noor Aldeen Alawad, Khalid M. O. Nahar.

In this paper, they used data mining and four machine learning algorithms (neural network, SVM, decision tree, KNN) to predict fungal toxicity. The Neural Network achieved 99.1% accuracy of data on 8,124 mushrooms.

3. Existing System

- The objective is to develop a system that can correctly detect edible mushrooms using 22 different mushroom characteristics. The challenge for the ML algorithms employed in the classification of the mushroom is to create a system that can reliably recognize and categorize edible mushrooms without endangering human health.
- Among the prominent stories resulting from the poisoning of mushrooms are, In Melbourne an unsettling series of events took place. Hours after consuming poisonous mushroom meal they soon transferred to a hospital tragically 2 passed away and another 2 remained in critical condition.
- In India from Meghalaya, three employees of the Institute of Science and Bio Resource (ISBR), were found dead. Police said the three are believed to have died due to mushroom poisoning.

4. Proposed System

Developing an innovative and accurate mushroom classification system is paramount for the safeguarding ofpublic health, the promotion of sustainable foraging practices, and the conversation of biodiversity. The purpose of this project is to utilize ML algorithms to develop a robust and user-friendly solutionthat not only prevents mushroom-related poisonings but also empowers foragers, culinary enthusiasts, and researchers with a reliable tool for responsible mushroom-related poisonings but also empowers foragers, culinary enthusiasts, and researchers with a reliable tool for responsible mushroom identification. By bridging the gap between technology and mycology, this proposed classification system seeks to make a meaningful contribution to global health, education, and environmental stewardship.

5. System Architecture

The system architecture design for the mushroom classification into edible or non-edible categories using machine learning algorithms is a sophisticated blueprint that intricately weaves together various componentsto create a robust and efficient framework. At the heart of this architecture is the data flow, starting with the input layer where mushroom images are uploaded for classification. This initiates a cascade of processes, beginning with a preprocessing module that standardizes and augments the raw images. The preprocessed datathen flows into the feature extraction layer.

Following feature extraction, the system incorporates a model training pipeline, where the machine learning model learns the complex patterns and relationships within the dataset. The training process involves iterations and adjustments of hyperparameters to optimize the model's performance. Once trained, the model transitionsinto the evaluation phase, where it is rigorously tested on a separate test dataset to assess its accuracy, precision, recall, and other relevant metrics. The performance evaluation offers important information about the model's capacity for generalization as well as its precision in dividing mushrooms into edible and inedible categories. The user interface module plays a pivotal role in user interaction, offering a seamless platform forusers to upload mushroom images and receive real-time classification results. This module serves as the bridgebetween the user and the underlying machine learning model, enhancing accessibility and usability. In summary, the system architecture for mushroom classification is a comprehensive and intricately designedframework that harmonizes data processing, model training, user interaction, scalability, security, and maintenance. This architecture serves as the backbone for a sophisticated and user-friendly mushroom classification system, providing accurate and reliable results for users navigating the diverse world of mushrooms.

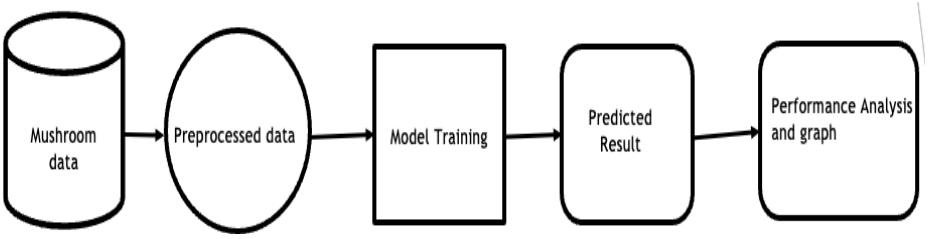

Figure 1: Proposed Research Model.

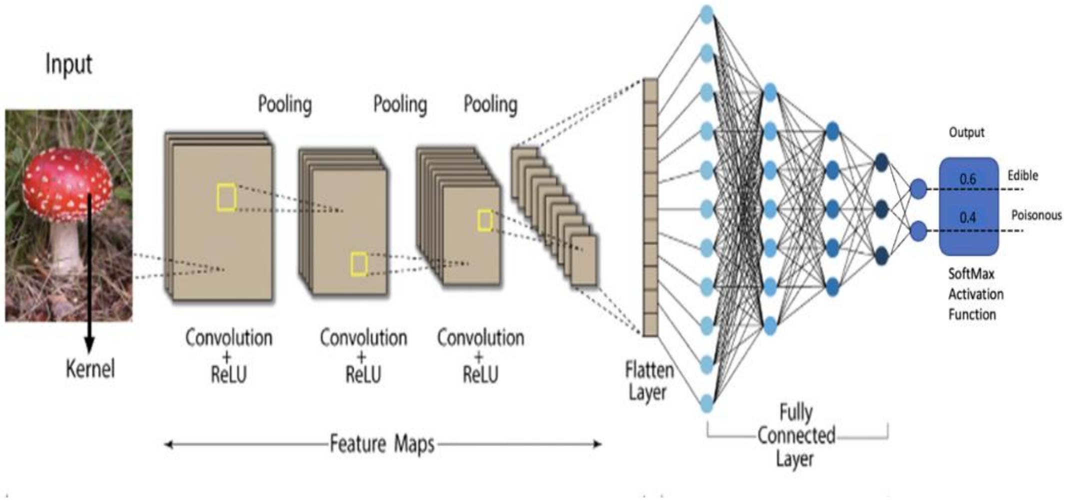

Figure 2: System Architecture Design of Convolution Neural Network

Layers of Convolution

CNNs have three main types of layers: full layer (FC), pooling layer, and convolution layer. When these layers are combined the CNN architecture is created. To build the model, we'll make use of the sequential model from the Keras library. The convolutional neural network will next be built by adding layers. The first 2 Conv2D layers used 32 filters with a 5.5 kernel size. The MaxPool2D layer will select the highest value from each 2X2 pixel region of the image when the pool size is set to (2,2). As a result, the image's dimensions will shrink by a factor of 2. The dropout rate in the dropout layer was kept constant at 0.25, which means that neurons chosen at random make up 25% of the population. With a few changes to the parameters, we apply these three layers again. To convert 2-D data into a vector in 1-D space, we then apply a flattened layer. This layer is followed by a dropout layer, a thick layer, and another thicker layer. By supplying a probability value, this layer estimates which of the seven alternatives has the highest likelihood. It does this by using the SoftMax activation function.

6. System Implementation

At this level, we attempt to evaluate the functionality of our application using Python as a programming language. The application is broken up into a variety of modules before being programmed for deployment.

1. Load the Dataset
2. Bringing in the required libraries
3. Getting the pictures back
4. Division of the dataset

5. Constructing the model

7. Experimental Results

Mean of Cross-value Accuracies of Mushroom Dataset

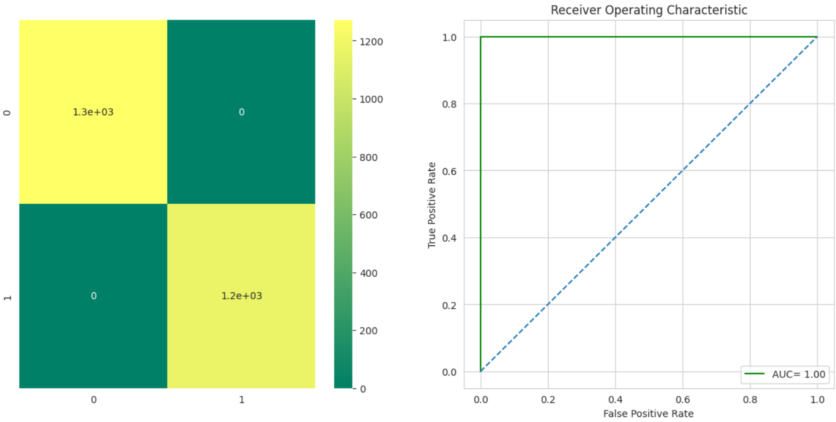

Figure 1: 0.9996481967375429 using a logistic regression model

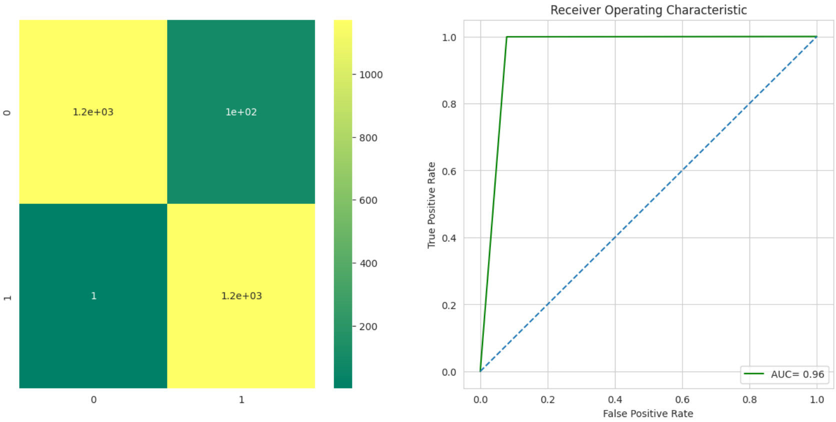

Figure 2: 0.952517079630684 using Gaussian Naïve Bayes

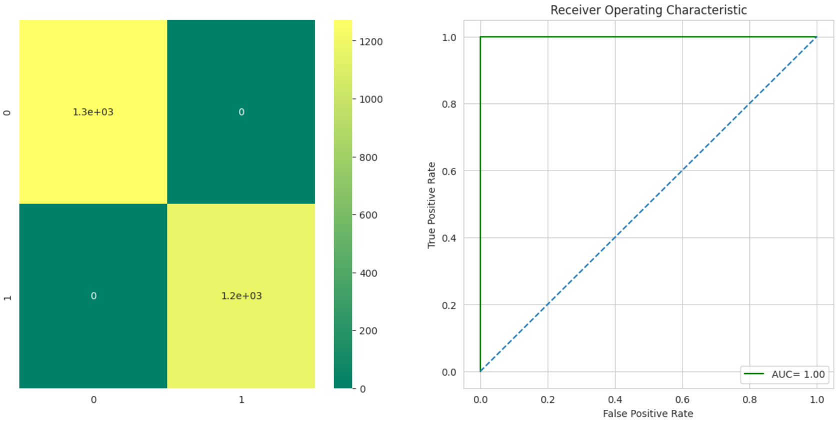

Figure 3: 0.9998239436619718 using the Decision Tree.

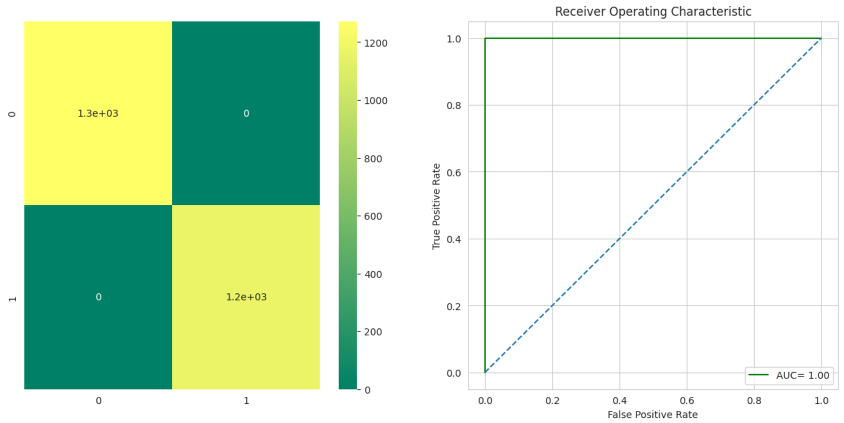

Figure 4: 1.0 using the Random Forest Classifier.

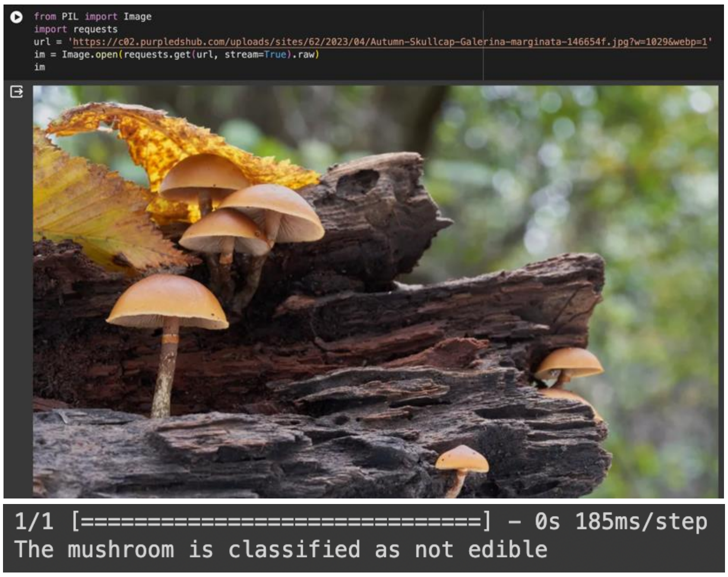

Figure 5: Output of given Mushroom image and showing it is deemed unfit for consumption

8. Conclusion and Future Scope

In this work, we investigated the usage of ML techniques in the image-based classification of mushroom edibility. We obtained encouraging findings in reliably differentiating between edible and harmful mushrooms by putting several ML models—such as convolutional neural networks (CNNs)—to use and evaluate them. The experiment showed that the accuracy and resilience of tasks involving the categorization of mushroom edibility could be greatly improved by utilizing deep learning architectures, such as CNNs. Models that have been trained on a variety of mushroom image datasets have acquired discriminative features that let them generalize effectively to new data, enabling accurate predictions. In addition, several difficulties, and factors to take into account, such as class imbalance, model interpretability, and dataset quality. By addressing these issues, the classification system's performance has increased, and our understanding of the fundamental variables affecting the prediction of mushroom edibility has also improved.

Future research and development could go in several directions. Adding more varied and high-quality photos of different mushroom species to the dataset would improve the model's ability to generalize even further. Investigating more sophisticated data augmentation methods may also be able to reduce overfitting and enhance the resilience of the model. Creating intuitive smartphone applications that make use of the trained model for real-time prediction of mushroom edibility could raise public knowledge and encourage safe mushroom foraging practices. The usefulness of such apps would be increased by adding more capabilities like location-based mushroom identification and toxicity data.

Description

1. All authors are conflict-free.
2. No author has conducted any experiments involving humans or animals that are included in this article.

9. References

1. V. A. Karampiperis and G. P. Potamias, "A comparative study of machine learning methods for the edible–poisonous mushroom classification problem," Expert Systems with Applications, vol. 36, no. 3, pp. 5887-5893, 2009.
2. M. N. Doğru and M. M. Tanrıöver, "Classification of edible and poisonous mushrooms using artificial neural networks and fuzzy logic," Expert Systems with Applications, vol. 39, no. 1, pp. 22-31, 2012.
3. T. K. Paul and P. M. Jawandhiya, "Classification of mushrooms as edible or poisonous using machine learning techniques," Procedia Computer Science, vol. 48, pp. 726-731, 2015.
4. J. R. Cano, M. G. C. A. Cuenca, and E. T. M. Martínez, "A machine learning approach for the classification of edible mushrooms," in International Work-Conference on the Interplay Between Natural and Artificial Computation, 2019, pp. 237-249.
5. L. Abdul-Wahab, S. A. Oonsivilai, and N. H. M. Sahari, "Comparison of machine learning algorithms for the classification of poisonous and edible mushrooms," International Journal on Advanced Science, Engineering and Information Technology, vol. 9, no. 1, pp. 42-47, 2019
6. V. Dvořák, L. Lhotská, and P. Španěl, "Mushroom classification based on machine learning and sensor data fusion," Sensors, vol. 21, no. 14, p. 4804, 2021.
7. M. E. A. M. Vázquez and J. L. S. Salido, "Comparison of machine learning algorithms for the classification of edible and poisonous mushrooms," in International Work-Conference on Bioinformatics and Biomedical Engineering, 2015, pp. 207-218.
8. D. K. Yadav, "Classification of edible and poisonous mushrooms using machine learning algorithms," International Journal of Computer Applications, vol. 180, no. 3, pp. 1-5, 2018.
9. S. N. F. A. Al-Hayali and H. A. Jalab, "Classification of mushrooms into edible and poisonous classes using machine learning algorithms," International Journal of Computer Applications, vol. 176, no. 7, pp. 36-42, 2019.
10. M. G. Venkatesan and S. S. Rani, "Classification of edible and poisonous mushrooms using machine learning algorithms," International Journal of Engineering and Technology, vol. 8, no. 1, pp. 78-82, 2016.
11. A. P. Jadhav, M. D. Rahane, and A. S. Pradhan, "Classification of mushrooms into edible and poisonous classes using machine learning algorithms," in International Conference on Intelligent Computing and Control Systems, 2017, pp. 841-846.
12. N. A. Singh and R. R. Singh, "A comparative study of machine learning algorithms for classification of edible and poisonous mushrooms," International Journal of Engineering Research & Technology, vol. 3, no. 11, pp. 3057-3062, 2014.

13. D. C. Pramanik and S. D. Jadhav, "Classification of mushrooms into edible and poisonous classes using machine learning techniques," International Journal of Computer Science and Information Technologies, vol. 7, no. 1, pp. 384-387, 2016.
14. K. R. Badea, D. H. Deaconu, and D. T. Burdescu, "A comparison of machine learning algorithms for the classification of edible and poisonous mushrooms," in International Conference on Advanced Data Mining and Applications, 2019, pp. 155-167.
15. S. S. Rani and M. G. Venkatesan, "Classification of edible and poisonous mushrooms using machine learning algorithms," in International Conference on Advances in Computing, Communications, and Informatics, 2016, pp. 1790-1795.
16. V. S. Gautam and S. R. Sawant, "Classification of edible and poisonous mushrooms using machine learning algorithms," International Journal of Computer Applications, vol. 132, no. 3, pp. 13-17, 2015.
17. S. V. Shinde and S. S. Apte, "Classification of edible and poisonous mushrooms using machine learning algorithms," International Journal of Computer Applications, vol. 134, no. 3, pp. 36-40, 2016.
18. S. R. Sawant and V. S. Gautam, "Classification of mushrooms into edible and poisonous classes using machine learning algorithms," in International Conference on Computer, Communication and Control (IC4), 2015, pp. 1-5.
19. S. K. Pal and S. Mitra, "Multispectral image analysis using a granular computing approach for classification of mushrooms into edible and poisonous classes," IEEE Transactions on Fuzzy Systems, vol. 16, no. 1, pp. 67-79, 2008.
20. D. L. Shankar, P. S. Hiremath, and K. S. Gurumurthy, "Classification of mushrooms into edible and poisonous classes using machine learning techniques," in International Conference on Communication and Signal Processing, 2016, pp. 1205-1209.