A REVIEW PAPER ON CNN APPROACHES FOR POISONOUS MUSHROOM IDENTIFICATION

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ABSTRACT

Mushrooms are popular due to their high nutritional value, which includes amino acids, polysaccharides, and other essential nutrients. However, eating poisonous mushrooms can cause serious health problems like nausea, vomiting, mental disorders, acute anemia, and even death. Every year, approximately 8,000 people suffer from mushroom poisoning, with 70 fatalities. With thousands of mushroom species, only about 900 are edible, making it difficult for those without specialized knowledge to distinguish between them. While many people believe that poisonous mushrooms are brightly colored, some dangerous species do not exhibit this characteristic. allowing for further advancements in mushroom toxicity detection and classification. To reduce the risks associated with eating toxic mushrooms, this study proposes using deep learning techniques to classify mushrooms as edible or poisonous based on image features such as color, shape, and texture. A dataset containing 5,127 edible and 3,163 poisonous mushroom images will be used for training, validation, and testing, with a 70% training, 15% validation, and 15% testing ratio. The ResNet50 algorithm, a deep learning architecture known for its performance in image classification, will be used. TensorFlow and Keras will be used to implement deep learning, NumPy and Pandas to manipulate data, Matplotlib to visualize, Scikit-learn to evaluate models, and Pillow to preprocess images. The model aims to provide accurate predictions while taking into account the benefits and side effects of various mushrooms. This solution, by automating the identification of toxic and edible mushrooms, will help reduce the risks associated with foraging. while also contributing to public safety.

Keyword:- *CNN, ResNet-50, Mushroom Classification, Toxic Mushroom Detection, Image Processing, TensorFlow, Keras, NumPy, Pandas, Matplotlib, Scikit-learn, and Pillow.*

1. INTRODUCTION

Mushroom cultivation is important for food, beverage, and medicinal purposes, as mushrooms contain essential nutrients such as vitamins, minerals, and proteins. However, distinguishing between edible and poisonous mushrooms is critical because toxic mushrooms can cause serious health problems, including liver failure, kidney damage, and even death. Despite similarities between some edible and poisonous species, CNN-based deep learning models such as ResNet-50 can effectively classify mushrooms as edible or poisonous using image analysis. This study uses TensorFlow and Keras for model development, NumPy and Pandas for data processing, and Matplotlib to visualize the results. Scikit-learn is used to assess the model's performance using metrics such as accuracy, precision, and recall, while Pillow helps with image processing tasks. The dataset is made up of mushroom images collected from various online platforms, ensuring a diverse representation of environmental conditions. The model benefits from transfer learning by utilizing ResNet-50's pre-trained capabilities, which improves its ability to accurately classify mushrooms. The proposed system aims to reduce the risk of mushroom poisoning, especially in areas where mushroom-related illnesses are common, by providing a dependable tool for foragers, mycologists, and the general public to safely identify mushrooms. This deep learning approach improves the safety of wild mushroom foraging, providing an important solution to the global problem of mushroom poisoning. This model, which uses advanced image classification techniques, has the potential to significantly reduce the number of accidental poisonings by providing an accessible, automated solution for identifying toxic species. It can be integrated into applications to help users quickly determine whether a mushroom is safe to eat. Furthermore, the model can be continuously improved by incorporating more diverse datasets and employing more advanced neural network architectures, resulting in increased accuracy and robustness. This study advances not only mushroom classification but also broader applications in food safety and public health, demonstrating the power of deep learning to solve real-world problems.

2. LITERATURE SURVEY

Recent research has concentrated on the classification of edible and poisonous mushrooms using deep learning and machine learning methods. Deep learning models, including InceptionV3, VGG16, and ResNet50, were used to classify mushroom images, with InceptionV3 achieving the highest accuracy of 88.40%. Convolutional Neural Networks (CNN) with architectures such as Inception-V3 were used to classify mushrooms with an accuracy of 92.7%, while other models such as VGG16, ResNet18, and Googlenet were combined with techniques such as bagging to improve accuracy to 93.1%. Additionally, region convolutional neural networks (CNN) were used to classify commonly found mushrooms, with an accuracy of 95.50%. Various neural network models, including AlexNet, ResNet-50, and GoogLeNet, were compared in terms of efficiency and test time, with results indicating that using augmented mushroom feature databases improved classification performance. Machine learning algorithms such as sNet, LeNet, AlexNet, cNet, and DCNN have been used to classify mushrooms, with the accuracy of various CNN architectures being evaluated. Various techniques, including Naïve Bayes, SVM, ANN, and decision trees, have been used for mushroom classification. Neural networks achieved 99.1% accuracy. Data mining techniques and machine learning models have produced promising results in the prediction of fungal toxicity, with high classification accuracy. These studies show that deep learning and machine learning can help distinguish between edible and poisonous mushrooms. TensorFlow, Keras, NumPy, Pandas, Matplotlib, Scikit-learn, and Pillow are popular tools for model development, data processing, and performance evaluation, making them useful for solving the mushroom classification problem. Using ResNet50 and these technologies, researchers are creating accurate models to reduce the risks associated with mushroom foraging..

3. PROBLEM STATEMET AND SOLUTION

3.1 Problem Statement

Mushrooms are a diverse group of fungi, some edible and others poisonous. However, because edible and poisonous mushrooms have similar appearances, distinguishing them can be difficult. Consuming poisonous mushrooms can cause serious health problems, such as headaches, allergies, and even death. The lack of expertise in identifying these mushrooms, as well as the potential risks of misidentification, necessitate the development of an automated system that can accurately classify mushrooms based on images. To distinguish between edible and poisonous species, this classification system should take into account a variety of characteristics such as color, shape and texture. Furthermore, the system should be able to provide information on the benefits and side effects of various mushrooms, making it useful for those who forage for them in the wild. The challenge is to create a model that can handle variations in mushroom features, lighting conditions, and backgrounds in images while still providing high classification accuracy.

3.2 Solution

To address this issue, we propose creating a deep learning-based classification system using the ResNet50 algorithm. This model will be trained on a dataset of mushroom images, with 70% set aside for training, 15% for validation, and 15% for testing. The dataset will consist of 5,127 edible mushroom images and 3,163 poisonous mushroom images, divided into appropriate training, validation, and testing sets. TensorFlow and Keras will be used to implement neural networks, NumPy and Pandas to manipulate data, Matplotlib to visualize, and Scikit-learn to evaluate the model. Pillow will be used for image pre-processing. The ResNet50 architecture, which is known for its ability to learn deeper representations, will be used to classify mushrooms based on their color, shape, and texture. The solution will not only determine whether mushrooms are edible or poisonous, but will also provide information about their benefits and potential side effects. The system aims to classify mushrooms with high accuracy, allowing users to make safer decisions when foraging for wild mushrooms. By leveraging these advanced technologies and deep learning algorithms, the proposed system will provide a dependable and scalable solution to the mushroom classification challenge.

Aspect	Details
Color	Varies by type (e.g., white, brown, red, yellow).
Shape	Caps (convex, flat, bell-shaped), stems, and gills.
Benefits	Edible mushrooms are nutrient-rich, contain antioxidants, and have medicinal properties.
Side Effects	Poisonous mushrooms can cause nausea, vomiting, organ failure, or even death.
Algorithm	ResNet-50, a pre-trained convolutional neural network for feature extraction and classification.
Technologies	TensorFlow, Keras, NumPy, Pandas, Matplotlib, Scikit-learn, Pillow.

Table-1 Details about poisonous mushroom detection

4. CONVOLUTION NEURAL NETWORK

Convolutional Neural Networks (CNNs) are powerful deep learning models that are commonly used for image classification tasks, making them ideal for distinguishing edible and poisonous mushrooms based on visual characteristics such as color, shape, and texture. This project uses a mushroom dataset divided into training, validation, and testing sets to create an efficient classification system. The ResNet50 algorithm, known for its deep architecture and skip connections, is used to extract detailed features and accurately distinguish edible from toxic varieties. TensorFlow and Keras enable model design and training, while NumPy and Pandas handle data preprocessing. Pillow is used for image processing, Matplotlib visualizes the results, and Scikit-learn assesses performance using metrics such as precision and recall. The model uses subtle visual cues such as mushroom color patterns and structural shapes to accurately predict their edibility. Automating this classification process greatly reduces the risk of consuming poisonous mushrooms, making it useful for foragers, culinary enthusiasts, and healthcare providers. By ensuring accurate identification, the system reduces the risk of mushroom poisoning while also improving safety and promoting informed mushroom consumption practices.

4.1 Resnet50 Algorithm

ResNet50 is a powerful deep learning algorithm that excels at image classification, particularly when it comes to analyzing complex features such as object color, shape, and texture. Its deep residual network architecture, which consists of 50 layers, effectively addresses the vanishing gradient problem through residual connections, allowing for the extraction of intricate patterns in images. This makes it ideal for distinguishing between edible and poisonous mushrooms based on subtle visual differences such as vibrant or muted colors, as well as structural variations in mushroom caps and stems. ResNet50 is implemented in this project with advanced technologies such as TensorFlow and Keras for model development, NumPy and Pandas for data preprocessing, and Pillow for image manipulation. Matplotlib is used to visualize results, and Scikit-learn evaluates model performance using precision and recall metrics. The dataset, which includes thousands of images of edible and poisonous mushrooms, is divided into three sets: training, validation, and testing, to ensure robust learning and accurate predictions. By utilizing ResNet50, this project provides a dependable and efficient solution to the critical challenge of mushroom classification, improving safety by reducing the risks associated with consuming toxic varieties. This approach not only improves identification accuracy, but it also helps to achieve the larger goal of informed and safe mushroom consumption. Furthermore, using transfer learning with ResNet50 enables faster convergence and improved performance, even with a smaller dataset, by leveraging pre-trained weights on large-scale image classification tasks. Furthermore, the model's ability to fine-tune specific layers during training allows it to better adapt to the distinct characteristics of mushroom images, increasing classification accuracy.

5. ARCHITECTURE

The architecture of this project is based on the ResNet50 deep learning model, which is intended for image classification tasks such as distinguishing between edible and poisonous mushrooms. ResNet50 employs a residual learning framework, which enables it to train deeper networks while avoiding the vanishing gradient problem. This architecture is made up of 50 layers of convolutional and residual blocks, allowing it to effectively extract complex features like color, shape, and texture from mushroom images. The ResNet50 model is trained using advanced technologies such as TensorFlow and Keras to identify and classify mushroom species based on visual characteristics. Pandas and NumPy are used to process the dataset, and images are augmented and preprocessed with Pillow. Matplotlib is used to visualize the model's performance, which includes accuracy and loss curves over epochs. Scikit-learn can help you evaluate model performance using metrics like precision, recall, and F1-score. The dataset is divided into three subsets: training, validation, and testing, ensuring that the model generalizes well to new data. This architecture allows for accurate identification of both edible and poisonous mushrooms, which improves consumer safety. The use of deep learning allows for large-scale mushroom classification with minimal side effects or human error.

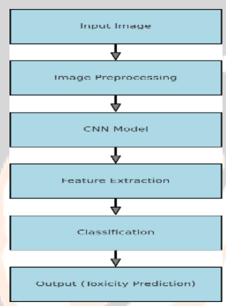

Fig-1 Architecture diagram of poisonous mushroom detection

6. ADVANTAGE AND LIMITATION

6.1 Advantage

1. Accurate Feature Extraction: ResNet-50 excels in identifying fine details such as color and shape.
2. Residual Learning: Its residual blocks address the vanishing gradient problem, allowing the model to train effectively even with deep architectures.
3. Scalability: It performs well on large datasets, handling high-dimensional image data efficiently.
4. Technology Integration: With tools like TensorFlow, Keras, NumPy, Pandas, Matplotlib, Scikit-learn, and Pillow, ResNet-50 enables streamlined preprocessing, visualization, and evaluation.
5. Generalization: It adapts well to variations in mushroom datasets, such as different textures and shapes, ensuring robustness.
6. Real-world Impact: By accurately predicting toxic mushrooms, it contributes to public health by reducing poisoning risks.

6.2 Limitations

1. Computational Demands: ResNet-50 requires high-performance hardware, which may not be readily available to all researchers.
2. Time-Intensive Training: Training on extensive datasets can be slow, requiring careful management of computational resources.
3. Hyperparameter Sensitivity: The model's performance depends significantly on tuning parameters like learning rate and batch size.
4. Dataset Dependency: Limited diversity in the dataset, such as consistent backgrounds or lighting, may reduce its ability to generalize to new environments.
5. Risk of Overfitting: Without proper regularization, the model may overfit smaller datasets.

6. Complexity: The deep architecture can be challenging for beginners to implement and debug effectively.

7. FUTURE WORK

Future research in mushroom classification systems can focus on improving the accuracy and efficiency of models such as ResNet-50 by expanding the dataset to include more diverse images of mushrooms from various environments. This expansion will improve generalization and the model's ability to detect a diverse range of mushrooms. Furthermore, using advanced image augmentation techniques, such as changing colors and shapes, could help the model distinguish between edible and poisonous mushrooms. Furthermore, combining ResNet-50 with newer architectures such as DenseNet or EfficientNet may enhance feature extraction capabilities while lowering computational requirements. For practical applications, integrating real-time classification models into mobile apps using TensorFlow, Keras, and Pillow would allow for instant mushroom identification while on the go, making it a valuable tool for both experts and non-experts in the field. TensorFlow Lite could enable faster processing on mobile devices while maintaining accuracy. Expanding the model's scope to include rare or endangered species and investigating multi-modal data, such as incorporating environmental or geographical information, could result in a more comprehensive detection system. Future research could investigate hybrid models that combine CNNs with Transformer-based architectures to improve both local and global feature extraction. Finally, by continuously improving the mushroom image dataset and adapting the model to more diverse real-world conditions, these systems could become more reliable, accessible, and effective in preventing poisonous mushroom consumption. Scikit-learn and Matplotlib are two technologies that can help with further analysis and visualization, paving the way for significant advances in this field.

8. CONCLUSION

To summarize, the use of deep learning algorithms such as ResNet-50, as well as tools such as TensorFlow, Keras, Numpy, Pandas, Matplotlib, Scikit-learn, and Pillow, provides a powerful approach to mushroom classification that allows for the accurate identification of edible and poisonous mushrooms. This system can efficiently classify mushrooms by processing and analyzing their distinct color, shape, and texture based on a large dataset of images. The addition of ResNet-50, a powerful Convolutional Neural Network (CNN), improves the model's ability to extract complex features and increase classification accuracy. The primary advantage of this system is its ability to reduce the risk of poisoning from eating toxic mushrooms by providing real-time identification assistance. However, challenges such as the system's reliance on high-quality image data, the need for extensive computational resources, and the possibility of misclassification in ambiguous cases must be addressed. Future work could include expanding the dataset, incorporating new mushroom species, and optimizing the model for mobile deployment with TensorFlow Lite. This would enable faster and more efficient mushroom identification in real-world scenarios. Furthermore, incorporating additional data sources, such as environmental factors or geographic information, may improve the model's robustness and generalizability. This deep learning-based mushroom identification system, with continuous improvement and refinement, holds significant promise for both public safety and the advancement of environmental classification using artificial intelligence.

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