LITERATURE SURVEY ON MUSHROOM CLASSIFICATION

BY

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1. A Deep Learning-Based Approach for Edible, Inedible and Poisonous Mushroom Classification - Nusrat Zahan et al., 2021

Advancements in Mushroom Classification:

- Mushroom classification is a crucial task in agriculture and food safety due to the risks associated with consuming poisonous mushrooms.
- Traditional methods relied on manual inspection or biochemical tests, which are time-consuming and not scalable.
- The emergence of deep learning and CNNs has enabled automated classification based on visual features, making real-time recognition feasible.

Transfer Learning & CNN Architectures:

- Deep convolutional neural networks have proven effective for handling natural image classification problems.
- Pre-trained CNNs (e.g., VGGNet, ResNet, Inception) can be fine-tuned for mushroom classification to reduce training costs and improve accuracy.
- Transfer learning helps in adapting models trained on large datasets (like ImageNet) to relatively small mushroom datasets.

Dataset and Data Augmentation:

- Authors created a mushroom dataset including edible, inedible, and poisonous categories.
- Images were sourced from real-world environments, improving robustness compared to curated datasets.
- Preprocessing steps included resizing, normalization, and data augmentation (flipping, rotation, color adjustments) to handle variability in shape, size, and background.

Frameworks and Tools:

- Implemented using TensorFlow/Keras for efficient model training.
- Standard CNN training pipeline applied with cross-entropy loss and adaptive optimizers (Adam/SGD).

Contribution of the Paper:

- Developed a CNN-based framework specifically for mushroom classification into three categories.

- Collected and prepared a realistic mushroom dataset that can be extended for future studies.
- Demonstrated that CNNs are effective in this domain, paving the way for automated food safety tools.

2. "Wild Mushroom Classification Based on Improved MobileViT Deep Learning" – Peng et al., 2023

Advancements / Context

- Wild mushrooms are difficult to classify due to fine-grained differences in appearance, variable lighting, backgrounds, and intra-class variation.
- Traditional methods (decision tree, SVM, naive Bayes) rely on handcrafted features and often fail with visual complexity in natural scenes.
- CNNs excel at extracting local image features but struggle with capturing global contextual information.
- Vision Transformers (ViTs) bring advantages in modeling global dependencies, but they often demand large datasets and lack the inductive biases of convolution.
- Hence, a hybrid architecture combining convolution and attention mechanisms is promising for fine-grained visual classification tasks like mushrooms.

Dataset & Data Augmentation

Two datasets used:

1. Mushroom dataset — includes 261 species categorized into edible, toxic, deadly, and conditionally edible.
2. MO106 dataset — 106 mushroom categories, about 29,100 images total, from FGVCx challenge and Wild Mushroom Observer data.

Data split: training and validation sets with ratio 8:2.

Augmentation techniques: random cropping, rotation, horizontal/vertical flipping; inference uses center cropping.

Figure 3. Images data augmentation.

Model Architecture & Methodology

Backbone: MobileViT (lightweight CNN + attention hybrid)

Enhancement modules:

• SE module embedded into residual blocks to emphasize channel features

• MDA (Multidimensional Attention): combines block attention (local windows) and grid attention (global span) in parallel, fusing them with original features.

• ASPP to fuse multi-scale features without downsampling, helping capture context from various receptive fields.

Additional structure: gMLP layers, skip connections, layer normalization to stabilize training and spatial gating.

Training details:

• Framework: Python 3.8, PyTorch 1.7.0

• Input image size: 224 × 224 (likely)

• Optimizer: AdamW

• Epochs = 300, batch size = 32, some weight decay, learning rate schedule (paper gives exact)

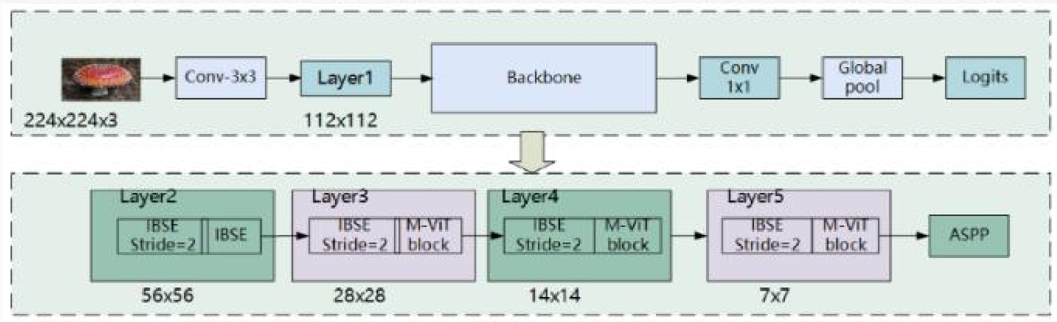
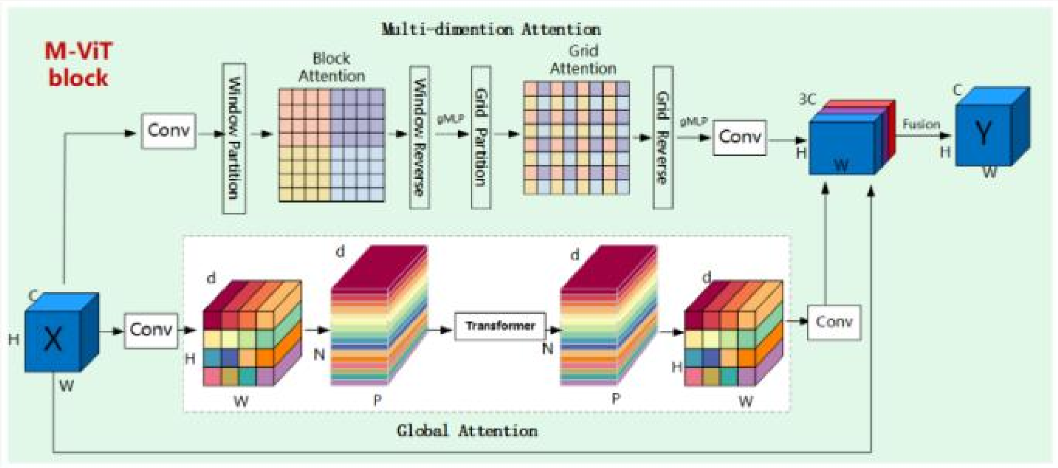


Figure 4. The M-ViT pipeline.

Figure 6. The M-ViT Block.



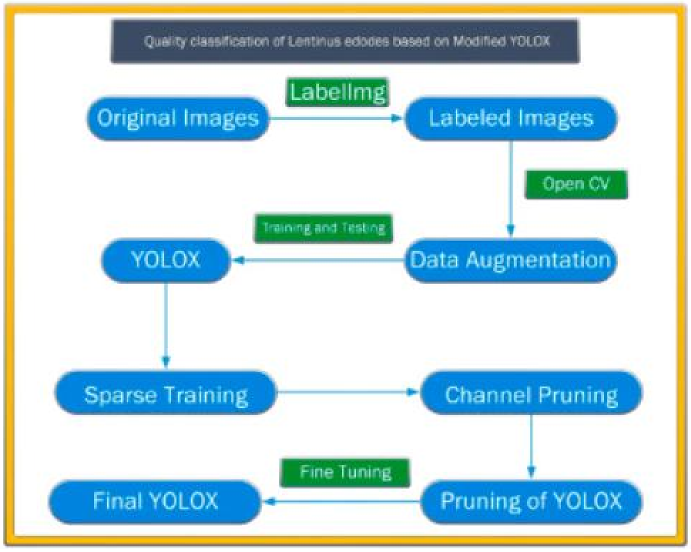
3. "Deep Learning Based Quality Classification of …" – Liu et al., 2022

Advancements / Context

- Quality inspection in many industries (e.g. manufacturing, food, agriculture) demands accurate and fast automated classification systems.
- Traditional computer vision / machine learning methods based on handcrafted features often fail under varying lighting, occlusions, or when subtle defects exist.
- Deep learning, especially convolutional neural networks (CNNs), has shown promise in visual quality inspection tasks.
- However, standard deep models may be bulky and computationally expensive, making deployment challenging on resource-constrained devices.

Dataset & Data Augmentation

- The paper focuses on a quality classification dataset (defect vs non-defect, or multiple quality levels) — the exact domain (product, material) is specified in the full text.
- Standard image preprocessing (resizing, normalization) is applied.
- To improve generalization, data augmentation (flipping, rotation, color jitter, etc.) is used.

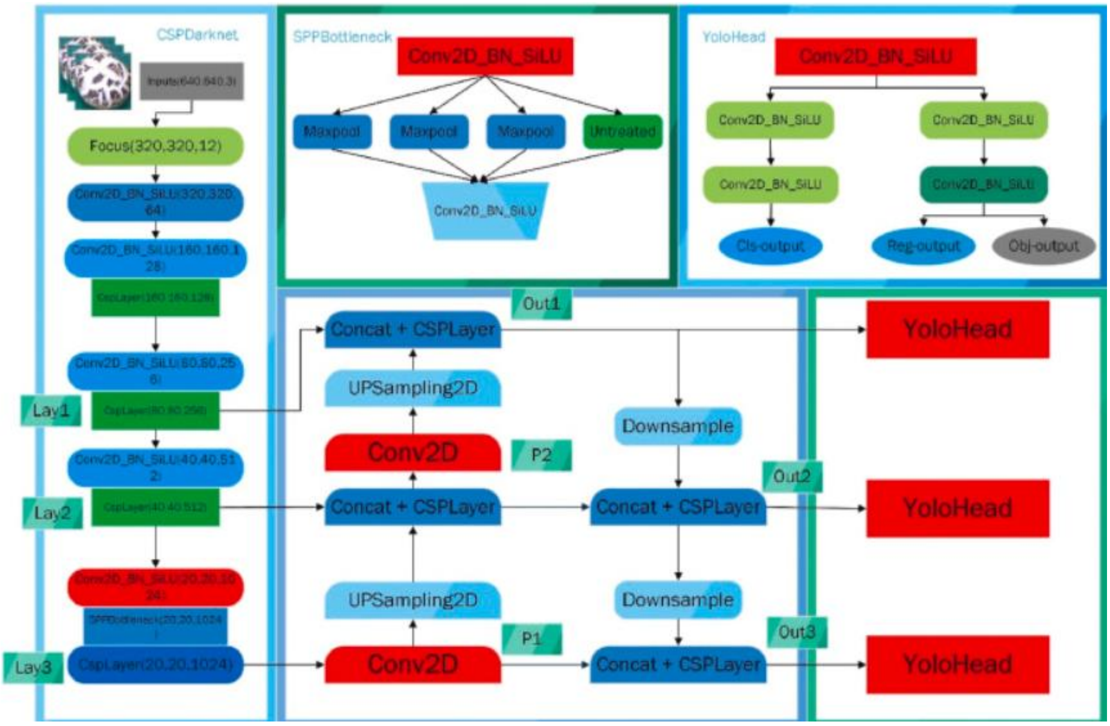


Insights, Discussion & Limitations

- Channel pruning can be an effective way to compress deep models for quality inspection tasks without drastic performance loss.
- There may be a trade-off: overly aggressive pruning can degrade accuracy. The balance between compression and performance needs careful tuning.
- The method shows promise for real-world applications (e.g. embedded systems, edge devices) due to lowered resource demands.
- Potential limitations include:
  - ✓ Pruning strategy may not generalize across all domains or defect types
  - ✓ Retraining / fine-tuning after pruning adds overhead
  - ✓ Extremely subtle defects might suffer from feature loss if pruning removes critical filters

Contribution & Implications

- A novel high-efficiency channel pruning framework tailored for quality classification integrated with YOLOX.
- Demonstrated that pruned models can match or nearly match unpruned accuracy with far lower computational cost.
- Facilitates deployment of deep inspection models in constrained hardware (e.g. edge, mobile devices).
- Sets direction for combining pruning + detection/classification models in industrial quality control.



4. "A New Deep Learning Model for the Classification of Poisonous and Edible Mushrooms Based on Improved AlexNet" – Ketwongsa et al., 2022

Advancements / Context

- Distinguishing edible vs poisonous mushrooms is difficult due to their very similar visual appearances, which can lead to fatal errors.
- Traditional classification using manual features or simple classifiers is often inadequate when mushrooms vary in shape, color, lighting, and background.
- Deep CNNs and transfer learning from large-scale pretrained models (e.g. AlexNet, ResNet, GoogLeNet) help leverage learned visual features for related tasks.
- Yet, running large pretrained networks in resource-constrained environments, or over small mushroom datasets, can be inefficient or prone to overfitting.

Transfer Learning & Model Design Choices

- The authors adopt transfer learning: they start from pretrained networks (AlexNet, ResNet-50, GoogLeNet) and compare them.
- They design an improved AlexNet variant:

- They remove the 4th and 5th convolutional layers of the original AlexNet to reduce depth and computational cost.
- They insert a GoogLeNet Inception module in lieu of the removed layers to better capture multi-scale features.
- The resulting architecture has three convolutional layers + one inception module + three fully connected layers.

Dataset & Data Augmentation

- They collected a dataset with 5 mushroom species, totalling 623 images, classed into edible (Amanita citrina, Russula delica, Phaeogyroporus portentosus) and poisonous (Inocybe rimosa, Amanita phalloides).
- Input images are sized 227 × 227 × 3.
- To mitigate overfitting, they apply data augmentation to expand 623 images into ~2,000 images.
- They use 10-fold cross-validation and split into training vs testing with a 90:10 ratio.

Insights, Discussion & Limitations

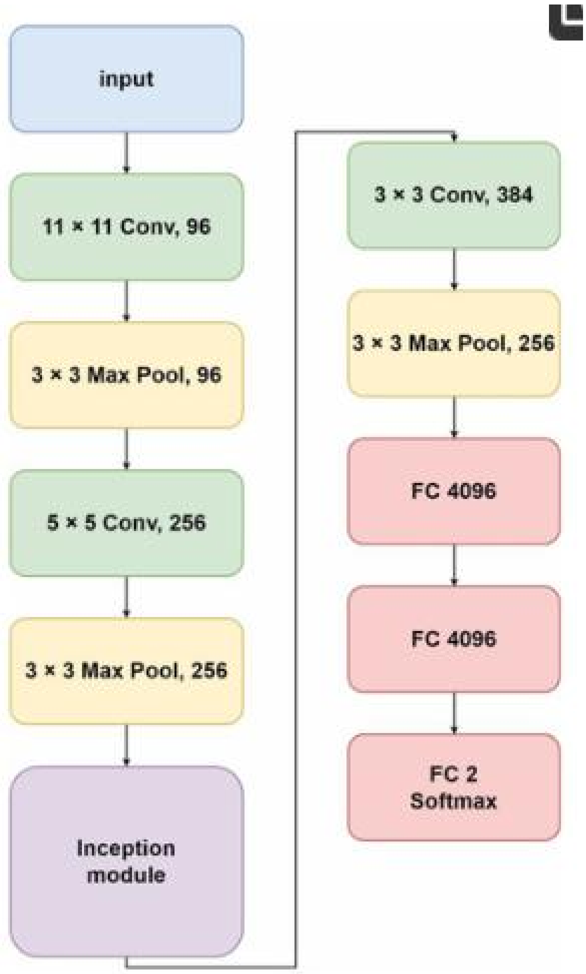
- The modified AlexNet + inception module balance accuracy vs computational cost: slightly lower accuracy than heavier models, but much faster.
- The trade-off: ResNet-50 and GoogLeNet yield marginally higher accuracy, but at much greater time cost, which may hinder real-time or resource-limited deployment.
- Class imbalance is a factor: poisonous class had fewer samples, possibly causing slightly lower recall in that category.
- The dataset is small (623 images); even after augmentation, generalization to new mushroom species or in-the-wild conditions is uncertain.
- Future extension suggested: include more species, varying backgrounds, lighting, and more diverse data.

Contribution & Implications

- Proposed an improved AlexNet-based architecture by pruning and integrating a GoogLeNet inception module to accelerate classification while retaining high accuracy.
- Achieved strong performance (98.50%) on mushroom classification with much faster training/testing time than heavier models.

➢ Demonstrated feasibility of lightweight deep models for edible/poisonous classification, which can be beneficial for practical deployment (mobile, edge devices).

➢ Provided a publicly available mushroom dataset (via Zenodo) to support future reproducibility and extension.



5. "Deep Learning Based Approach for Classification of Mushrooms" – Demirel & Demirel, 2023

Advancements / Context

➢ Deep learning methods, particularly CNNs, have achieved remarkable success in image recognition tasks.

➢ Mushroom classification in natural environments poses challenges: varying backgrounds, lighting, occlusions, and morphological similarities between species.

- The goal is to find an effective deep learning model capable of classifying mushrooms in their natural habitat (rather than in controlled conditions) using naturally captured images.

Dataset & Data Acquisition

- Images were sourced from iNaturalist, labeled by experts, showing mushrooms in their natural environments (diverse backgrounds)
- The dataset is split into training, validation, and test sets.
- No further details in abstract about augmentation, class counts, or species distribution in the article's abstract section.

Methodology / Model Architecture

- The authors evaluate well-known pretrained CNN architectures and propose a variant they call "MobileNetV2_GAP_flatten_fc" as their best model.
- "GAP" likely refers to Global Average Pooling and "flatten_fc" suggests adding a fully connected layer(s) after flattening.
- The model is fine-tuned on the mushroom dataset to optimize feature extraction and classification.

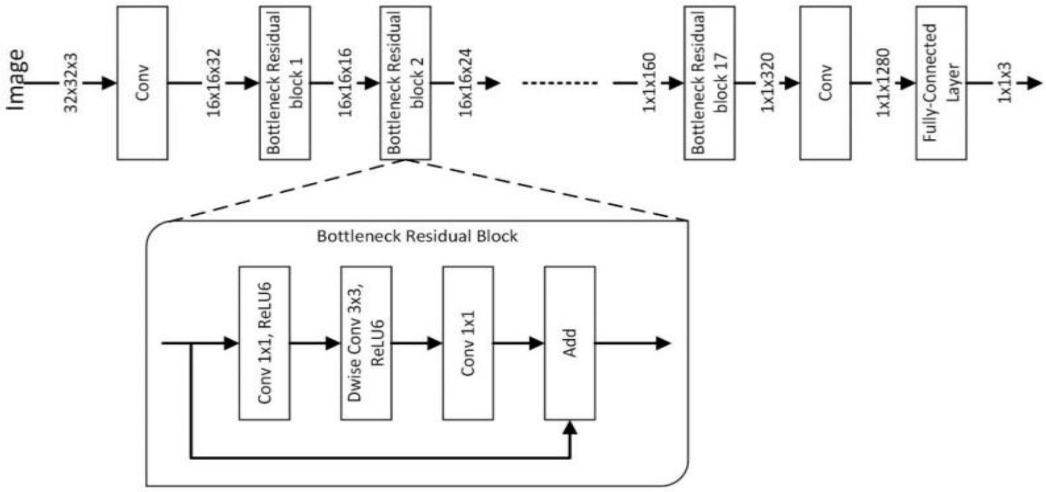
Insights, Discussion & Limitations

- The extremely high training accuracy suggests possible overfitting; the drop to ~97–98% on validation/test indicates the model generalizes fairly well in natural habitat images.
- Using iNaturalist's real-world images gives more realistic evaluation compared to lab-condition datasets, strengthening the practical utility of their model.
- The article suggests that the proposed training method enhances feature extraction and learning capabilities of the network in this domain.
- Potential limitations (not explicitly stated in the abstract) might include: imbalanced classes, limited number of species, varying image conditions beyond what the model has seen, and computational overhead for deployment in field systems.

Contribution & Implication

- They provide an experimental benchmark for mushroom classification in natural habitat conditions using real-world images.
- Their variant MobileNetV2_GAP_flatten_fc shows strong performance, demonstrating that lightweight architectures (like MobileNetV2) can be effective in this domain when adapted carefully.

- Their comparison with other pretrained models helps highlight what works best in the wild mushroom context.
- The work has applications for mushroom hunters, pharmacology, and reducing poisoning risk by aiding identification in uncontrolled settings.



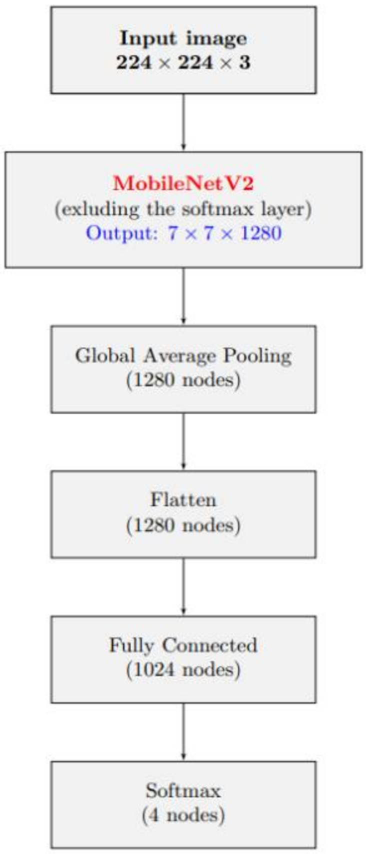
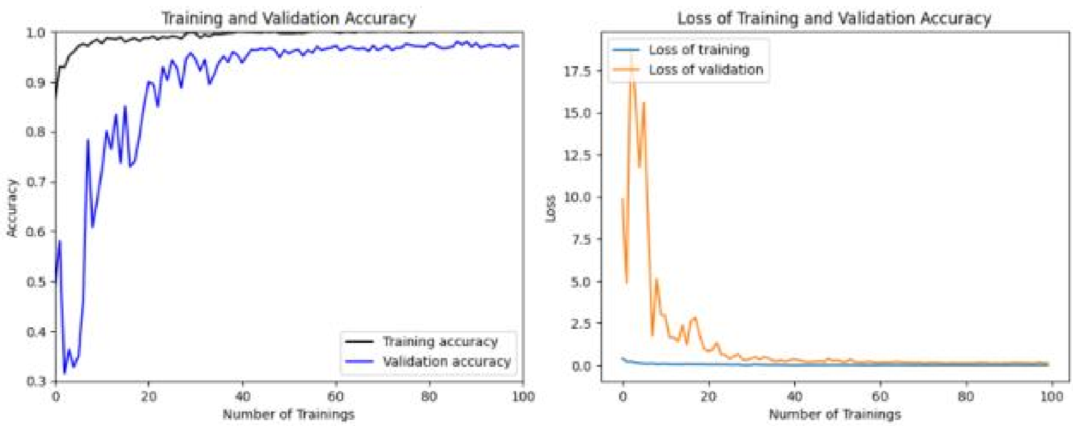


Figure 4. *MobileNetV2_GAP_flatten_fc*



6. "Deep Learning Based Approach for Classification of Mushrooms" by Yağmur Demirel and Gözde Demirel (2023)

Advancements / Context

- Deep Learning in Image Recognition: Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in image classification tasks.
- Challenges in Mushroom Classification: Identifying mushrooms in their natural habitats is challenging due to varying backgrounds, lighting conditions, occlusions, and morphological similarities among species.
- **Objective:** Develop an effective deep learning model capable of classifying mushrooms in their natural environments using images captured under real-world conditions.

Dataset & Data Acquisition

- Source: Images were sourced from iNaturalist, labeled by experts, showcasing mushrooms in their natural environments with diverse backgrounds.
- Dataset Split: The dataset was divided into training, validation, and test sets.
- Details: The abstract does not provide specific information regarding data augmentation, class distribution, or species count.

Methodology / Model Architecture

- Pretrained CNN Architectures: The study evaluates several well-known pretrained CNN models.
- Proposed Model: A variant named "MobileNetV2_GAP_flatten_fc" is introduced as the best-performing model.

- GAP: Global Average Pooling
- flatten_fc: Flattening followed by fully connected layers
- Fine-tuning: The model was fine-tuned on the mushroom dataset to optimize feature extraction and classification performance.

Insights, Discussion & Limitations

- Overfitting Concern: The exceptionally high training accuracy suggests potential overfitting; however, the model generalizes well with validation and test accuracies around 97–98%.
- Real-World Evaluation: Utilizing iNaturalist's real-world images provides a more realistic evaluation compared to controlled lab-condition datasets, enhancing the practical applicability of the model.
- Training Methodology: The proposed training approach enhances the feature extraction and learning capabilities of the network in this domain.

Potential Limitations:

- Imbalanced class distribution
- Limited number of species
- Varying image conditions beyond the model's training scope
- Computational overhead for deployment in field systems

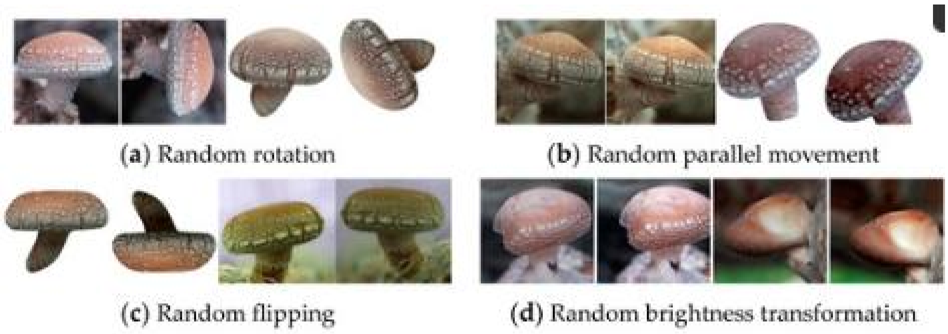
Contribution & Implication

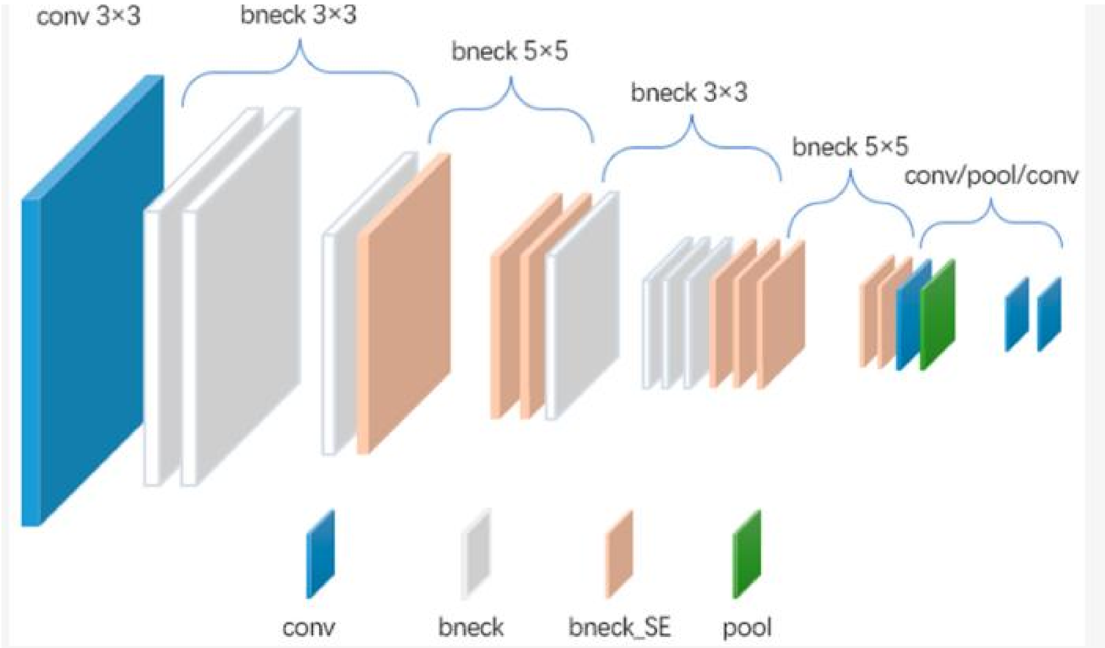
- Benchmarking: Provides an experimental benchmark for mushroom classification in natural habitat conditions using real-world images.
- Model Effectiveness: Demonstrates that lightweight architectures like MobileNetV2 can be effective in this domain when adapted appropriately.

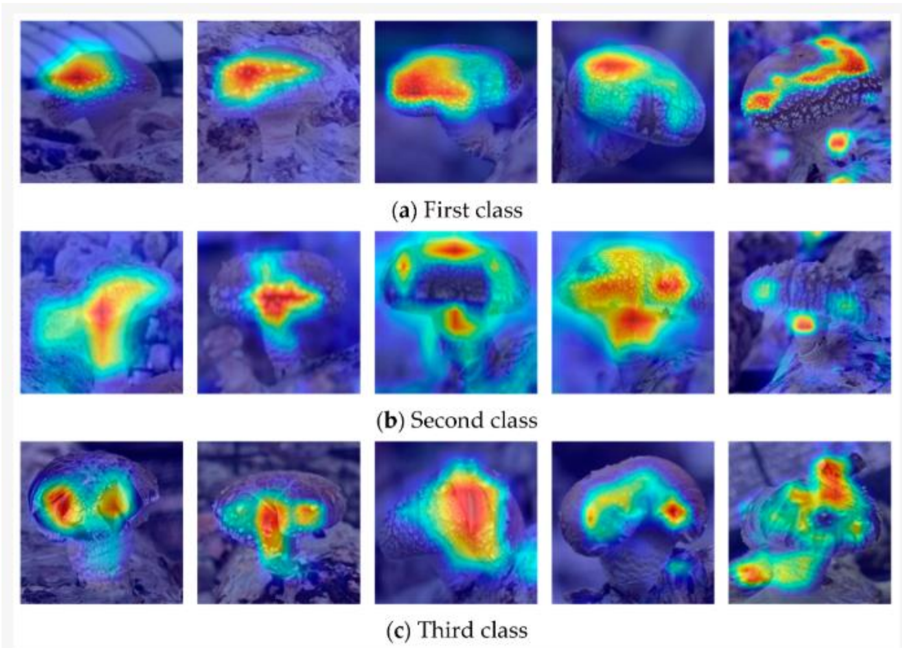
Practical Applications:

- Assists mushroom hunters in identifying species in the wild
- Supports pharmacological studies by distinguishing between edible and toxic mushrooms
- Aids in reducing poisoning risks by providing accurate identification in uncontrolled settings

(a) Original image (b) Background removed image


(a) Random rotation
(b) Random parallel movement
(c) Random flipping
(d) Random brightness transformation


conv 3×3
bneck 3×3
bneck 5×5
bneck 3×3
bneck 5×5
conv/pool/conv
conv
bneck
bneck_SE
pool


(a) First class
(b) Second class
(c) Third class

7. "Critical Analysis of Machine Learning and Deep Learning Models for Mushroom Classification" by Akashdip Neogi (2024)

Advancements / Context

- Importance of Mushroom Classification: Accurate identification of mushrooms is crucial to prevent the consumption of toxic species, which can lead to severe health issues.
- Challenges in Classification: Mushrooms often share similar morphological features, making it difficult to distinguish between edible and poisonous varieties. Factors such as soil type, climate, and developmental stages further complicate identification.
- Technological Shift: Traditional identification methods have limitations, prompting the exploration of machine learning (ML) and deep learning (DL) techniques to enhance classification accuracy.

Dataset & Data Acquisition

- Dataset Composition: The study utilized a dataset comprising images of mushrooms, though specific details regarding the dataset's size, source, and preprocessing steps are not provided in the abstract.
- Data Augmentation: To address the challenges posed by limited data, data augmentation techniques were likely employed, though specifics are not detailed in the abstract.

Methodology / Model Architecture

Machine Learning Models Evaluated:

- Random Forest: A traditional ensemble learning method known for its robustness and interpretability.
- Support Vector Machine (SVM): A supervised learning model effective in high-dimensional spaces.

Deep Learning Models Evaluated:

- MobileNetV2: A lightweight convolutional neural network (CNN) architecture optimized for mobile devices.
- ResNet50 & ResNet101: Deep residual networks that address vanishing gradient problems in deep architectures.

- VGG16: A deep CNN known for its simplicity and effectiveness in image classification tasks.
- Custom CNN: A tailored convolutional neural network designed for the specific task of mushroom classification.
- Transfer Learning: Pretrained models were fine-tuned on the mushroom dataset to leverage existing knowledge and improve classification performance.
- Hyperparameter Optimization: Techniques were employed to identify the optimal settings for each model, enhancing their performance.

Contribution & Implication

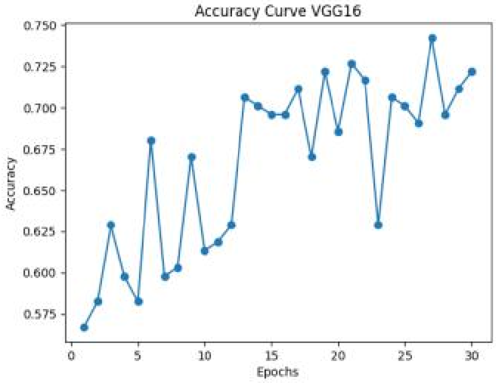
- Practical Applications: The research provides a foundation for developing tools that can assist in the real-time identification of mushrooms, potentially reducing the risk of poisoning.
- Advancement in Classification Techniques: Demonstrates the effectiveness of deep learning models, particularly MobileNetV2, in classifying mushrooms, highlighting the potential of these models in mycology.
- Future Research: Encourages further exploration into more diverse datasets and multi-modal approaches to improve classification accuracy and reliability.

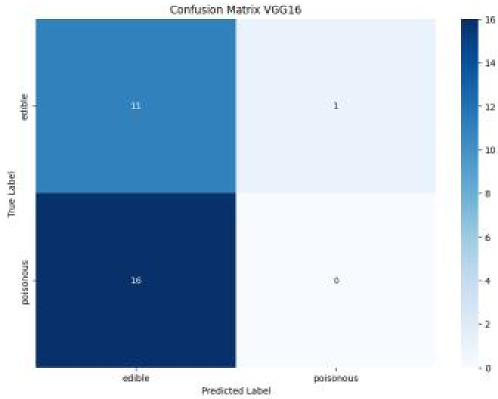
Model Name	Layer Name	No of Layers Present
VGG16 (Base Model)	Convolutional Layer	13
VGG16 (Base Model)	Fully Connected Layer	3
Custom Layers	Conv2D	2
Custom Layers	BatchNormalization	2
Custom Layers	MaxPooling2D	1
Custom Layers	GlobalAveragePooling2D	1
Custom Layers	Fully Connected Layer	4 (3 Dense + 1 Output)
Custom Layers	Dropout	3

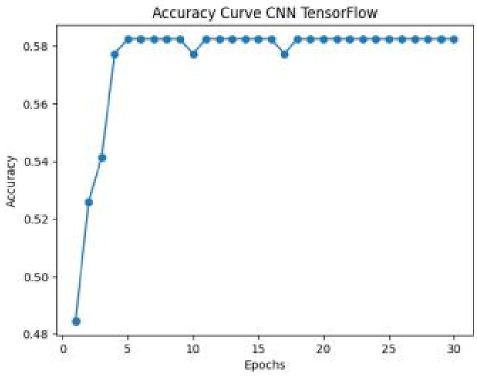
Table 5: Model Architecture, VGG16

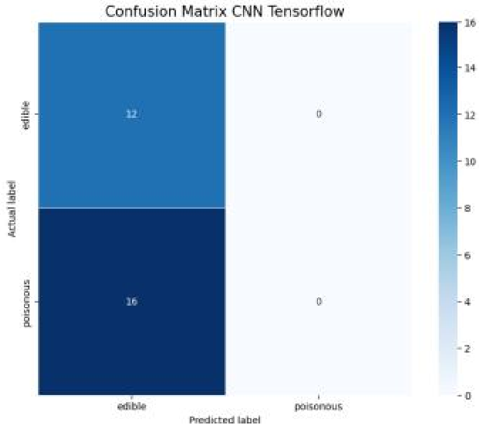
Layer Name	No of layers present
Convolutional layer	1
Residual Blocks	51
Final Convolutional layer	1
Global Average Pooling layer	1
Fully Connected layer	1

Table 6: Model Architecture, MobileNetV2


Accuracy Curve VGG16
Accuracy
Epochs


Confusion Matrix VGG16
True Label
Predicted Label
edible
poisonous
11
1
16
0


Accuracy Curve CNN TensorFlow
Accuracy
Epochs


Confusion Matrix CNN Tensorflow
Actual label
Predicted label
edible
poisonous
12
0
16
0