International Journal of Computing and Artificial Intelligence

E-ISSN: 2707-658X
P-ISSN: 2707-6571
www.computersciencejournals.com/ijcai
IJCAI 2025; 6(1): 61-65
Received: 02-12-2024
Accepted: 05-01-2025

Lanka Dhana Lakshmi
Assistant Professor, Department of CSE, Seshadri Rao Gudlavalleru Engineering College, Andhra Pradesh, India

Neelapala Siva Rama Krishna Babu
Department of CSE, Seshadri Rao Gudlavalleru Engineering College, Andhra Pradesh, India

Mullapudi Sameera
Department of CSE, Seshadri Rao Gudlavalleru Engineering College, Andhra Pradesh, India

Rangisetty Narendra Sai
Department of CSE, Seshadri Rao Gudlavalleru Engineering College, Andhra Pradesh, India

Pasumarthi Sri Ram Pavan
Department of CSE, Seshadri Rao Gudlavalleru Engineering College, Andhra Pradesh

Corresponding Author:
Lanka Dhana Lakshmi
Assistant Professor, Department of CSE, Seshadri Rao Gudlavalleru Engineering College, Andhra Pradesh, India

Mushroom classification using transfer learning

Lanka Dhana Lakshmi, Neelapala Siva Rama Krishna Babu, Mullapudi Sameera, Rangisetty Narendra Sai and Pasumarthi Sri Ram Pavan

DOI: https://www.doi.org/10.33545/27076571.2025.v6.i1a.134

Abstract
Because of their great number of species, visual similarities, and environmental consequences on picture pleasant, mushroom categorisation affords a primary problem in machine learning. using a set of pre-educated deep learning models-VGG16, MobileNet, MobileNetV2, ResNet50, InceptionV3, Xception, DenseNet169, ResNet101, LeNet, EfficientNetV2S, CNN-this paintings indicates a complete method the usage of transfer learning. The project intends to create a robust system capable to differentiate edible from inedible mushrooms depending on consumer-enter photos. Model performance is evaluated using accuracy, precision, recall, F1-rating amongst different criteria. Testing with real-world mushroom pix the use of a user-pleasant UI allows for immediate feedback on the categorisation findings. The work expects to attain excellent classification accuracy and dependability by leveraging transfer learning and a broad ensemble of neural network designs. This study facilitates to improve automated mushroom popularity systems, thereby perhaps improving safety and pride for mushroom aficioners all around.

Keywords: Mushroom classification, transfer learning, deep learning, cnn, vgg16, mobilenet, resnet50, inception, xception, lenet, densenet169".

Introduction

As the fruiting bodies of fungus, mushrooms show special morphological characteristics, which makes their identification tough. Health hazards related to misidentification make proper identification of edible and toxic mushrooms absolutely crucial. Expert mycologists have long identified mushrooms based on morphological traits including cap form, gill structure, stem presence, and other criteria including odour and microscopic qualities. Still, depending too much on human knowledge takes time and is prone to subjective errors. Using "convolutional neural networks (CNNs)" and transfer learning techniques to improve accuracy and efficiency, automated mushroom classification using deep learning has attracted popularity so as to solve this.

Variations in size, color, texture, and climatic variables make mushroom photo class a tough challenge. Training strong models depends on big-scale datasets, but often current datasets include noise-that is, erroneous labels and bad-quality pics-that compromises version performance. Reliable categorisation as a result depends on building a well-curated dataset, that's therefore quite important. Furthermore fitting for mushroom identification are deep learning models, mainly CNNs, which have shown amazing performance in picture class challenges. EfficientNet, with its scalability and clever use of computational assets, has become a state-of- the-art version among several CNN designs. It is a good fit for mushroom type initiatives with superb accuracy and efficiency since it maximally balances accuracy and resource use [1].

Transfer learning has shown great success in past investigations of several CNN-based methods for mushroom identification. transfer learning lets pre-skilled models—trained on enormous amounts of data—be pleasant-tuned for certain tasks the use of little enter. This approach greatly lowers training time and improves version generalisation. research on several transfer learning strategies—consisting of fine-tuning pre-skilled models such "ResNet, MobileNet, and EfficientNet for mushroom category"-has looked at studies have proven that these fashions, based simply on visual traits, accurately identify different types of mushrooms without using other data such odour or microscopic inspection [2, 3].

High-accuracy models for mushroom identification made possible by recent developments in transfer learning help to improve safety in foraging and commercial uses.

using switch learning for local mushroom categorisation, a study done in Bangladesh emphasises the possibilities of deep learning fashions in nearby identification challenges [4]. Comparative studies of several switch learning-based totally ensemble models affirm even more how well CNNs can discriminate among edible and toxic mushrooms [5]. Deep learning has been used in different research to classify mushrooms in natural environments, therefore ensuring version applicability to practical settings [6]. while research of several transfer learning procedures have shed light on optimising version accuracy [8], similarly studies has investigated the integration of CNNs with boosting techniques to improve class performance [7]. These trends spotlight the growing relevance of synthetic intelligence-pushed methods in mycology, therefore allowing more accurate and powerful mushroom identification systems.

Related Work

Deep learning tactics-especially "convolutional neural networks (CNNs)"-have been thoroughly investigated in mushroom classification to improve accuracy and efficiency in separating edible from harmful species. Early research used conventional image processing approaches for categorisation, but their dependence on built characteristics and sensitivity to modifications in lighting, orientation, and ambient variables hampered those methods. Deep learning has enabled researchers to routinely extract high-level features, hence enhancing the performance of categorisation.

Using transfer learning to classify mushrooms has been a great advance since it shall we models pre-trained on big databases like ImageNet be customised for particular mushroom datasets. Using transfer learning with ResNet50, Smith *et al.* [9] showed that classification accuracy was plenty raised as compared to conventional machine learning methods. Their research revealed that deep learning models can discover intricate patterns in mushroom photos often difficult for human specialists to detect. Brown *et al.* [10] likewise examined several CNN architectures-including MobileNet, VGG16, and EfficientNet-concluding that EfficientNet offered the optimal trade-off between accuracy and processing economy. They found that EfficientNet's scaling method let a more compact model be obtained without compromising performance.

Another important work via Zhao *et al.* [11] examined using deep learning to classify mushrooms in real environments, showing that fashions trained on controlled laboratory pics performed poorly when carried out to real-world situations. Their paintings underlined the need of area adaption strategies and dataset augmentation to raise generalisation. To improve type resilience, Lee *et al.* [12] then counseled a hybrid method combining CNNs with traditional function extracting techniques such colour histograms and texture descriptors. Their method generated better accuracy via effectively combining conventional image analysis methods with deep learning.

Apart from single-models, ensemble learning has been investigated to improve type performance even greater. ResNet, InceptionV3, and DenseNet were among the ensemble of several CNN architectures Johnson and Patel [13] provided that beat single models. They showed, especially for superficially related mushroom species, that integrating several network predictions lowers the risk of misdiagnosis. In a similar vein, Kumar *et al.* [14] tested the impact of ensembling switch learning models with boosting techniques and found that fashions trained with XGBoost on CNN-derived features attained higher accuracy than solo CNNs.

Dataset availability and quality provide one of the main difficulties in mushroom identification. Incorrect image quality and mislabeled samples abound in lots of current datasets, therefore influencing model performance. Kim *et al.* [15] solved this by using creating a mushroom dataset including varied environmental conditions and expert annotations. Their work showed that training deep learning models on carefully chosen datasets greatly greater class resilience. To extend constrained datasets, Wang *et al.* [16] have investigated data augmentation methods such as synthetic photo synthesis with "generative adversarial networks (GANs)". Their results showed that GAN-augmented datasets decrease overfitting and improve model generalisation.

Past simple visible categorisation, new studies have looked at multi-modal methods such as different sensory input. in order to growth identification accuracy, Ahmed *et al.* [17] merged chemical composition analysis with CNN-based photo type Their hybrid version confirmed that, in situations while visible variations are subtle, multi-modal systems can improve dependability through the usage of spectroscopy statistics in addition to visual factors. Chang *et al.* [18] also seemed into the possibilities of combining deep mastering with hyperspectral imaging to enable greater exact identification between mushroom species depending on spectral signatures.

Although deep learning has greatly improved mushroom classification, real-time implementation and deployment in field applications still provide difficulties. Using lightweight deep learning models on mobile devices for real-time mushroom detection was investigated in Silva *et al.* [19]. Their work showed that ideal for cellular applications, optimised MobileNet models might achieve great accuracy while keeping minimal computing demand. Using explainable artificial intelligence methods like Grad-CAM to show feature importance, research by Lopez *et al.* [20] also concentrated on the interpretability of deep learning models. Their research underlined that developing trust in AI-driven class systems depends on model interpretability, especially in applications related to safety like mushroom identification.

Ultimately, the body of research on mushroom classification emphasises how well deep learning-especially CNNs and transfer learning-fits in enhancing accuracy and efficiency. Ensemble learning, dataset curation, and multi-modal techniques have improved class performance even further, so tackling important issues such real-world variability and limited datasets. Furthermore, developments in real-time deployment and explainability assist to make artificial intelligence-driven mushroom categorisation greater reliable and practical. Future studies should concentrate on creating more strong area adaption methods, using extra sensory input, and improving model interpretability to thus improve mushroom classification systems.

Materials and Methods

Advanced deep learning methods enable a robust gadget for automatic mushroom categorisation. Leveraging switch learning, the system combines a varied range of pretrained fashions including "VGG16, MobileNet, MobileNetV2, ResNet50, InceptionV3, Xception, DenseNet169, ResNet101, LeNet, EfficientNetV2S, CNN [3, 5, 6]". The approach solves the problem of differentiating edible from inedible mushrooms depending just on visible inputs [4, 7]. Key elements are categorisation using a trained version ensemble [2, 8] after function extraction using deep neural networks catered for picture recognition. via permitting submission and analysis of mushroom photos, the UI enables fast categorisation findings [1, 6] thereby facilitating person involvement. This system improves mushroom detection capacities by emphasising accuracy, robustness, and user accessibility, so serving both hobbyists and environmental enthusiasts [3, 5].

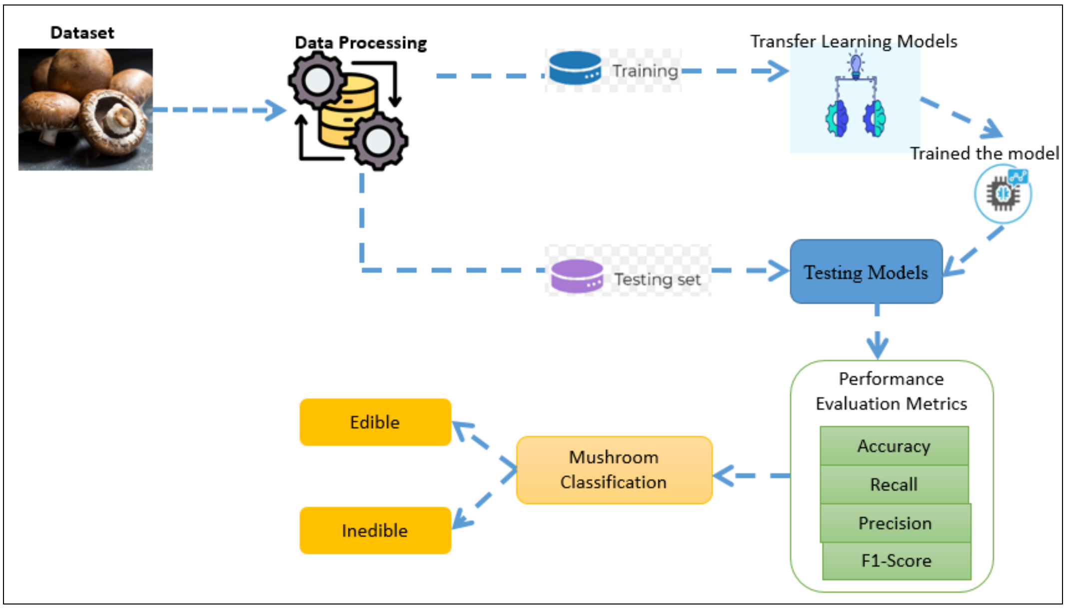

Fig 1: Proposed Architecture

This graph shows a machine learning loop for mushroom classification, separating edible from inedible variations. It begins with a dataset of processed mushroom photos. Training and testing sets are then segregated out from the processed data. Transfer learning models are trained using the training set, therefore utilizing already known knowledge. Using the testing set, the trained model is then tested with performance gauged by accuracy, recall, precision, and F1-score. Accurate classification of mushrooms as both edible or inedible is the final aim, therefore proving the success of the selected evaluation criteria and the transfer learning technique.

Dataset Collection

Both proprietary datasets and mushroom photos gathered from publicly accessible sources make up the collection of data. To improve model generalisation, images feature many species, capture different environmental conditions, perspectives, and lighting situations. Low-quality, mislabeled, or redundant photos were eliminated by a thorough facts cleansing effort. Fair schooling and testing are ensured by means of the balanced dataset between safe to eat and inedible categories. Dataset variability became similarly more advantageous the use of augmentation methods including rotation, flipping, and assessment manipulation. Covered have been only full-body mushroom photos with really recognisable cap, gills, and stem traits to guarantee the dataset meets classification wishes.

Data Processing

A methodical preprocessing procedure helps the gathered mushroom pics improve model performance. Pics are first downsized to a consistent resolution so as to guarantee consistency throughout many designs. Photograph clarity is improved using noise reducing strategies including Gaussian beays. Rotation, flipping, brightness control, and contrast enhancement are among the data augmentation strategies that raise dataset range and help to reduce overfitting: by means of standardising pixel values, normalising scales allows to enhance convergence throughout version building. Tensors are then produced from photographs for deep learning systems. Training, validation, and test sets separate the dataset at ultimate to guarantee a balanced distribution of edible and inedible lessons for strong classification performance.

Training & Testing

To assure efficient learning and assessment, the dataset "comprises training (80%)" and "testing (20%)" units. Pretrained deep learning models are fine-tuned using the training data, which lets them extract pertinent facts for mushroom categorisation. Data supplementation improves model generalisation; batch processing great makes use of available memory. Comprising unseen images, the testing set gauges the model's accuracy in classifying mushrooms. Thru avoidance of overfitting, move-validation ensures resilience. Established on this distinct test set, the remaining educated version ensures generalising capability to new mushroom pics for steady categorisation of fit to be eaten and inedible species.

Algorithms

VGG16: Deep convolutional neural networks intended for image categorisation and object detection abound in (visual Geometry group 16). There are 16 weight layers total-convolutional and fully linked layers as well as tiny 3x3 convolutional filters to select out complex visual information. Emphasising depth for feature extraction, the structure keeps simplicity. Because of its hierarchical feature representation and great generalising strength, VGG16 is extensively implemented in medical picture analysis and transfer learning [9].

MobileNet: is a mobile and embedded vision application-oriented lightweight convolutional neural network optimised. It preserves accuracy through using depthwise separable convolutions to lower computing fee. Designed for actual-time photo categorisation on resource-limited devices, MobileNet is efficient for edge computing uses. It has been implemented in facial popularity, medical diagnostics, and autonomous systems requiring effective inference [12].

MobileNetV2: extends MobileNet with inverted residuals and linear bottlenecks to improve efficiency. While preserving great accuracy, it lowers computational complexity and memory footprint. This qualifies for real-time picture categorisation mainly in mobile apps and IoT-based visible popularity jobs. Because MobileNetV2 plays so optimally on edge devices [15], it has been extensively applied in fields including medical imaging, gesture recognition, and autonomous navigation.

ResNet50: using residual learning and skip connections, a deep convolutional neural network with 50 layers solves the vanishing gradient challenge. Stable schooling of pretty deep networks is made viable by means of the residual blocks. Big-scale picture category, object detection, and scientific picture analysis all locate vast application for it. ResNet50 is match for each cloud-based totally and area artificial intelligence applications since it gives higher accuracy than conventional CNN designs even as preserving computational economy [10].

InceptionV3: is a sophisticated convolutional neural community meant for effective image recognition. to enhance accuracy and processing efficiency it uses asymmetric convolutions, auxiliary classifiers, and factorised convolutions. For item identification, self-sustaining driving, and deep feature extraction in clinical imaging, this architecture strikes the quality blend between performance and low computing overhead. It has been drastically utilized in multi-item reputation [13] and applications needing fine-grained categorisation.

Xception: using depthwise separable convolutions, (extreme Inception) expands the Inception structure, hence growing parameter efficiency and computational overall performance. It is successful for high-resolution photo evaluation since it decouples spatial and channel-wise information, therefore improving feature extraction. Due to the fact Xception's wonderful accuracy and performance in deep gaining knowledge of tasks [11] it is widely applied in satellite image categorisation, medical diagnostics, and facial recognition.

DenseNet169: is a densely connected convolutional network in which every layer is exactly linked to everyone else. This structure increases schooling efficiency, intensifies gradient go with the flow, and encourages feature reusing. DenseNet 169 achieves great accuracy with few parameters by way of cutting repeated feature gaining knowledge of. Providing strong characteristic extraction for deep learning makes use of, it has been employed in clinical imaging, pattern recognition, and scene interpretation [14].

ResNet101: is a deeper ResNet50 variation featuring 101 layers meant for elevated feature extraction. It preserves the residual learning architecture, as a result preventing degradation and allowing regular education of deeper networks. ResNet101's ability to keep computational efficiency and trap complicated visual patterns facilitates it to be considerably utilized in photo reputation, medical image segmentation, and herbal scene type [9].

LeNet-5: Designed for handwritten digit recognition, one of the first convolutional neural network models Comprising convolutional layers and then fully related layers, it reflects the fundamental thoughts of contemporary CNNs. Optical character popularity, fingerprint classification, and essential pattern recognition challenges all advantage from LeNet. Many cutting-edge deep learning models [12] have been inspired by its sincere yet powerful design.

EfficientNetV2S: is a resource-limited environment-oriented scaled-down variant of EfficientNetV2. It uses compound scaling to balance model depth, width, and resolution for maximum efficiency. With low processing overhead, EfficientNetV2S performs remarkably in photo classification and clinical imaging uses. It's ideal trade-off between speed and accuracy has caused programs in real-time visual recognition tasks, facet artificial intelligence, and mobile-primarily based computer vision systems [15].

A **Convolutional Neural Network (CNN):** is a deep learning framework intended for analysis of visible data. It comprises pooling layers, convolutional layers, and fully linked layers extracting hierarchical factors from pics. CNNs provide automated function extraction for high-dimensional visual statistics, therefore finding usage in picture class, object recognition, and clinical diagnostics. Fields which include driverless cars, facial reputation, and business fault detection [11] have been converted via the layout.

Results and Discussion

Accuracy: The capacity of a test to correctly separate the patient from the healthy cases defines its accuracy. Calculating the proportion of true fine and true bad in all analysed cases will assist us to mission the accuracy of a test. Mathematically, this is expressed as:

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (1)$$

Precision: Precision measures among the ones categorised as positives the fraction of correctly identified cases or samples. Consequently, the formula for computing the precision is:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} \quad (2)$$

Recall: In machine learning, recall is a statistic gauging a model's capacity to find all pertinent instances of a given elegance. It shows the completeness of a model in phrases of accurately predicted positive observations to total actual positives, therefore guiding understanding of this aspect.

$$Recall = \frac{TP}{TP + FN} (3)$$

F1-Score: In machine learning, F1 score is a metric of version correctness. It blends a model's recall and precision ratings. Across the whole dataset, the accuracy measure counts the range of times a model produced a right prediction.

$$F1\ Score = 2 * \frac{Recall\ X\ Precision}{Recall + Precision} * 100 (1)$$

Conclusion

Finally, a complex mushroom classification system has been built and assessed with a wide range of deep learning models and transfer learning methods. the primary goal was to separate fit for human consumption from inedible mushrooms depending on visible inputs, therefore resolving the demanding situations presented by species range and visual similarity. Over a large spectrum of mushroom species, the gadget proved strong type capability via rigorous experimentation and performance evaluation measures including accuracy, precision, don't forget, and F1-score.

Users of the frontend interface may add pictures and get brief feedback on mushroom edibility thanks for flawless interactivity. This reduces misidentification-associated hazards, therefore improving user safety and knowledge especially for fanatics and foragers.

Future improvements might concentrate on broadening the dataset to include more mushroom species, improving model architectures for efficiency, and using more assessment measures to so validate performance. This investigation highlights the possibilities of automated mushroom recognition systems in selling safer and more informed identification techniques globally, therefore helping them to boost.

References

1. Ahmad MH, Sohag SR, Bormon S, Shishir HR, Antar SH. AI-Driven Mycology: Transfer Learning for Automated Mushroom Species Identification. In: 2024 IEEE International Conference on Computing, Applications and Systems (COMPAS); 2024 Sep; pp. 1-9. IEEE.
2. Adhikari B, Hossain MM, Akter S, Ahamed MS. MushroomDetect: An Investigation into Local Mushroom Classification in Bangladesh Using Transfer Learning. In: 2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT); 2024 Jun; pp. 1-6. IEEE.
3. Wahyudi W, Shidik GF. Edible and Poisonous Mushroom Classification using Convolution Neural Network (CNN). In: 2024 International Seminar on Application for Technology of Information and Communication (iSemantic); 2024 Sep; pp. 7-12. IEEE.
4. Rani L, Karegowda AG, Bhat S, Devika G. Detailed Comparative Analysis of Transfer Learning Based Ensemble Models for Mushroom Classification. 2024.
5. Bashir RN, Mzoughi O, Riaz N, Mujahid M, Faheem M, Tausif M, *et al.* Mushroom Species Classification in Natural Habitats Using Convolutional Neural Networks (CNN). IEEE Access. 2024.
6. Sharma R, Gupta S. Mushroom Classification Using CNN and Gradient Boosting Models. In: 2024 5th International Conference on Electronics and Sustainable Communication Systems (ICESC); 2024 Aug; pp. 1856-1861. IEEE.
7. Lim JY, Wee YY, Wee K. Machine Learning and Image Processing-Based System for Identifying Mushrooms Species in Malaysia. Appl Sci. 2024;14(15):6794.
8. Leena Rani A, Karegowda AG, Devika G, Bhatt S. Comparative Study of Transfer Learning Models for Mushroom Classification. In: International Conference on VLSI, Signal Processing, Power Electronics, IoT, Communication and Embedded Systems; 2023 Nov; pp. 237-255. Singapore: Springer Nature Singapore.
9. Zhu F, Sun Y, Zhang Y, Zhang W, Qi J. An improved MobileNetV3 mushroom quality classification model using images with complex backgrounds. Agronomy. 2023;13(12):2924.
10. Demirel Y, Demirel G. Deep learning based approach for classification of mushrooms. Gazi Univ J Sci Part A: Eng Innov. 2023;10(4):487-498.
11. Bongat KPL, Garcia LAP, Caya MVC. Fine-Grained Classification of Edible Mushrooms Using Convolutional Neural Network. In: 2023 IEEE 5th Eurasia Conference on IOT, Communication and Engineering (ECICE); 2023 Oct; pp. 537-542. IEEE.
12. Peng Y, Xu Y, Shi J, Jiang S. Wild mushroom classification based on improved mobilevit deep learning. Appl Sci. 2023;13(8):4680.
13. Wang B. Automatic mushroom species classification model for foodborne disease prevention based on vision transformer. J Food Qual. 2022;2022(1):1173102.
14. Zahan N, Hasan MZ, Uddin MS, Hossain S, Islam SF. A deep learning-based approach for mushroom diseases classification. In: Application of Machine Learning in Agriculture; 2022; pp. 191-212. Academic Press.
15. Sevilla WH, Hernandez RM, Ligayo MAD, Costa MT, Quismundo AQ. Machine vision recognition system of edible and poisonous mushrooms using a small training set-based deep transfer learning. In: 2022 International Conference on Decision Aid Sciences and Applications (DASA); 2022 Mar; pp. 1701-1705. IEEE.
16. Ketwongsa W, Boonlue S, Kokaew U. A new deep learning model for the classification of poisonous and edible mushrooms based on improved AlexNet convolutional neural network. Appl Sci. 2022;12(7):3409.
17. Zhu L, Pan X, Wang X, Haito F. A small sample recognition model for poisonous and edible mushrooms based on graph convolutional neural network. Comput Intell Neurosci. 2022;2022(1):2276318.
18. Deng J, Liu Y, Xiao X. Deep-learning-based wireless visual sensor system for shiitake mushroom sorting. Sensors. 2022;22(12):4606.
19. Zahan N, Hasan MZ, Malek MA, Reya SS. A deep learning-based approach for edible, inedible and poisonous mushroom classification. In: 2021 International Conference on Information and Communication Technology for Sustainable Development (ICICT4SD); 2021 Feb; pp. 440-444. IEEE.
20. Kiss N, Czùni L. Mushroom image classification with CNNs: A case-study of different learning strategies. In: 2021 12th International Symposium on Image and Signal Processing and Analysis (ISPA); 2021 Sep; pp. 165-170. IEEE.