

DEEP LEARNING APPROACH TO MUSHROOM SPECIES CLASSIFICATION

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1 INTRODUCTION

Fungi identification is an increasingly critical task, with implications in food security, industrial use, conservation efforts, and biosafety. However, visual and image classification of fungi is a difficult task due to the wide variety of species (Lücking et al., 2020).

Nearly 87% of Ontario’s land is Crown Land, filled with expansive forests and a diverse array of plant species. Among these, mushrooms stand out as both common and challenging to identify, due to their wide variety and subtle differences between species. Thus, identification is particularly important because some species are edible and others are highly poisonous, which could pose a risk to foragers and nature enthusiasts.

Our project developed a deep learning model based on a convolutional architecture to accurately identify macrofungi (fungi with large bodies) based on their genus. Deep learning formed a suitable choice for this task, as it constitutes a powerful and accurate method for image recognition and classification tasks, including in ecological settings (Schneider et al., 2019).

We used the MIND.Funga dataset described in Drechsler-Santos et al. (2023), which has approximately 17 000 images of more than 500 species of fungi spanning 216 genera. This dataset is well-suited for our project, as it is built primarily for use in deep classification models. Images are also curated to be of a high quality and are labelled by species.

Our code can be found at this GitHub repository. It contains Jupyter notebooks with pre-processing, baseline, main model, and evaluation code.

2 BACKGROUND & RELATED WORK

3 DATA PROCESSING

The original dataset contains images of 509 classes. Many species have a small number of images associated with them, insufficient for training a deep learning model. To mitigate this, we grouped images into larger “buckets” based on their genus to reduce the number of classes to XX classes, which increases the number of images per class. Genera form an ideal way to group images together, as species of the same genus share physical characteristics and the same root name (first word in the species name) (Hollister et al., 2023).

Once this combination is done, we take the top 10 genera with the most images to form an intermediate dataset of 6131 images. We then randomly split the dataset into training, validation, and testing sets with a 75%, 15%, and 10% split, respectively. This split ensures the model has enough data to train on, while ensuring validation and testing better reflects its performance.

Finally, we apply data augmentation techniques described by Shorten & Khoshgoftaar (2019) solely to the training set, to avoid poisoning the validation and testing sets. We applied flips, rotations (90, 180, 270 degrees), Gaussian noise, and random erasing (of black rectangular regions). These manipulations were chosen as non-destructive methods that would not alter the image’s quality or classification. As mushrooms are identifiable based on visual traits, preserving key details is necessary to distinguish between genera. As our model is agnostic to colour, colour space transformations were not applied.

Our final dataset contains 16 962 training images, 3379 validation images, and 2324 testing images. To generate a usable set, we save a comma-separated value (CSV) file for each set, containing the image path and corresponding label. We also serialize the dataset into a binary Pickle object.

4 ARCHITECTURE

5 BASELINE MODEL

Our baseline model is a random forests classifier trained with scikit-learn on the same dataset as our deep learning model. Decision tree classifiers, like random forests, are generally well-suited for multiclass problems (Gall et al., 2012). We follow the same processing steps as the primary model, including a train-test split of 75%-25%, data augmentation on the training set, feature extraction, training, and evaluation.

We apply feature extraction on grayscale images with histogram of oriented gradients (HOG), an edge extraction descriptor algorithm (N. Dalal & B. Triggs, 2005-06-20/2005-06-25), computed with scikit-image. As random forests does not automatically perform feature extraction (compared to deep convolutional networks), this step is done to provide the model with a more effective set of features to learn from. We compute HOG features on both the training and testing set with default parameters, in line with the process outlined by Dutta (2024). We also use default hyperparameters for training, with the exception of the number of estimators, set to 500, which suggests is an optimal number of trees for increasing accuracy.

6 QUANTITATIVE RESULTS

7 QUALITATIVE RESULTS

8 EVALUATION ON NEW DATA

9 DISCUSSION

10 ETHICAL CONSIDERATIONS

Many machine learning models rely on the “unauthorized uses of copyrighted” data for training purposes. This broadly results in infringement of the intellectual property rights and personal interests of the data owners (Sobel, 2021). The dataset used in this project, MIND.Funga, is publicly licensed under a permissive copyleft license (CC BY NC 3.0) (Drechsler-Santos et al., 2023). Images were sourced from contributions from the public and academics. However, the organizing project does not disclose that public contributions will be released under this license (Drechsler-Santos et al., 2023), suggesting that the dataset may contain images that were not intended to be shared under this license as a result of inadequate informed consent.

The dataset also mostly contains images of tropical fungi from Brazil, with a small subset (approximately 500 out of 14 000) of the globally recorded number of fungi species (Lücking et al., 2020). This results in a model that is primarily representative of Brazilian fungi species. As some fungi species can be poisonous, any practical real-world applications of our model may result in misclassifications, which may result in harm to users that rely on the model. This is a significant ethical concern, as the model may be used by individuals who are not experts in mycology, and may not be able to identify the potential risks of consuming certain fungi species.

REFERENCES

- Elisandro Ricardo Drechsler-Santos, Fernanda Karstedt, Thiago Zimmermann Loureiro Chaves, Mahatmā Tittton, Kelmer Martins da Cunha, Eloísa Leopoldo, Genivaldo Alves-Silva, Diogo Rezende, Thiago Kossmann, Emerson Luiz Gumboski, and Aldo von Wangenheim. MIND.Funga, July 2023.
- Srijan Dutta. Random Forest for Image Classification Using OpenCV. *GeekforGeeks*, 2024.
- Juergen Gall, Nima Razavi, and Luc Van Gool. An Introduction to Random Forests for Multi-class Object Detection. In Frank Dellaert, Jan-Michael Frahm, Marc Pollefeys, Laura Leal-Taixé, and Bodo Rosenhahn (eds.), *Outdoor and Large-Scale Real-World Scene Analysis*, pp. 243–263, Berlin, Heidelberg, 2012. Springer Berlin Heidelberg. ISBN 978-3-642-34091-8.
- Jack D. Hollister, Xiaohao Cai, Tammy Horton, Benjamin W. Price, Karolina M. Zarzeczny, and Phillip B. Fenberg. Using computer vision to identify limpets from their shells: A case study using four species from the Baja California peninsula. *Frontiers in Marine Science*, 10, 2023. ISSN 2296-7745.
- Robert Lücking, M. Catherine Aime, Barbara Robbertse, Andrew N. Miller, Hiran A. Ariyawansa, Takayuki Aoki, Gianluigi Cardinali, Pedro W. Crous, Irina S. Druzhinina, David M. Geiser, David L. Hawksworth, Kevin D. Hyde, Laszlo Irinyi, Rajesh Jeewon, Peter R. Johnston, Paul M. Kirk, Elaine Malosso, Tom W. May, Wieland Meyer, Maarja Öpik, Vincent Robert, Marc Stadler, Marco Thines, Duong Vu, Andrey M. Yurkov, Ning Zhang, and Conrad L. Schoch. Unambiguous identification of fungi: Where do we stand and how accurate and precise is fungal DNA barcoding? *IMA Fungus*, 11(1):14, July 2020. ISSN 2210-6359. doi: 10.1186/s43008-020-00033-z.
- N. Dalal and B. Triggs. Histograms of oriented gradients for human detection. In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05)*, volume 1, pp. 886–893 vol. 1, 2005-06-20/2005-06-25. ISBN 1063-6919. doi: 10.1109/CVPR.2005.177.
- Stefan Schneider, Graham W. Taylor, Stefan Linquist, and Stefan C. Kremer. Past, present and future approaches using computer vision for animal re-identification from camera trap data. *Methods in Ecology and Evolution*, 10(4):461–470, April 2019. ISSN 2041-210X. doi: 10.1111/2041-210X.13133.
- Connor Shorten and Taghi M. Khoshgoftaar. A survey on Image Data Augmentation for Deep Learning. *Journal of Big Data*, 6(1):60, July 2019. ISSN 2196-1115. doi: 10.1186/s40537-019-0197-0.
- Benjamin Sobel. Taxonomy of Training Data: Disentangling the Mismatched Rights, Remedies, and Rationales for Restricting Machine Learning. In Jyh-An Lee, Reto Hilty, and Kung-Chung Liu (eds.), *Artificial Intelligence and Intellectual Property*, pp. 0. Oxford University Press, February 2021. ISBN 978-0-19-887094-4. doi: 10.1093/oso/9780198870944.003.0011.