**Project group B proposal**

*Deep Learning Modelling for the Image Recognition of Mushrooms –*

*A Case study based on Convolutional Neural Network*

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1. Motivation

The motivation for studying the recognition of mushroom types using a convolutional Neural Network (CNN) stems from the recent growth in mushroom foraging as a hobby recently, especially since the onset of the pandemic.[1]

Image recognition analysis was chosen as it is an interesting field with many real-world applications and presents an exciting opportunity to test the ability of CNN in recognising a wide variety of mushroom types, many of which appear similar.

This is also an active area of research so the opportunity to compare our work with other academic papers also guided our choice of topic for this project. Classification of poisonous/edible species may also be possible for this project, but our primary focus will be simply recognizing the species of mushrooms with reasonable accuracy.

1. Research question

How accurately can we recognize mushroom species using CNN?

1. Literature review
2. **Advancements in Image Classification using Convolutional Neural Network**[2]

This paper lays out the different components of convolutional neural networks and shows the advancements in CNNs over the years from LeNet-5 to SENet.

The CNN structure outlined here is multiple convolution and sub-sampling or pooling layers, followed by at least 1 fully connected layer and an output layer.

In terms of comparing the advancements of CNNs, AlexNet, ZFNet, and VGGNet follow the architecture of conventional CNN like LeNet-5, but have much bigger networks. They find that models that combine inception module and residual blocks to a conventional CNN model, such as GoogleNet and ResNet gain better accuracy than simply stacking the same blocks together. DenseNet reuses features to strengthen the feature propagation in the network. CapsNet is a model that achieved great results on MNIST but doesn’t do as well on high resolution images. SENet performed well on high resolution images and could be a viable CNN for tasks requiring strong discriminative features, which may be useful in ruling out certain mushroom species for our project.

1. **Benchmark Analysis of Representative Deep Neural Network Architectures**[3]

This paper contains an in-depth look at most deep neural networks used for image recognition. Some of the performance indicators used in comparing these networks include recognition accuracy, model complexity, computational complexity, memory usage, and inference time. A subset of these metrics will likely be used in informing our choices in the CNN used for our mushroom species recognition problem. One interesting observation made here is the top-1 accuracy of each network plotted against the images per second of various deep neural networks, finding that NASANet-A-Large and SENNet-154 performed the best.

1. **Fungi Recognition: A Practical Use Case** [4]

The paper presents a system for the visual recognition of 1394 fungi species based on deep convolutional neural Networks. The authors utilize test and training sets on their data, to validate their findings.

The distribution of images per class is highly unbalanced in the training set, while the validation set distribution is uniform. The initial accuracy obtained was 48.8% and the authors utilized different data feature techniques to improve this accuracy. Among the techniques utilized we must cite: an ensemble 6 CNN, different architectures, hyperparameter tuning, image augmentation, or adjusting predictions to new class priors due to the unbalanced dataset.

The best performing experiment is the ensemble of the 6 fine-tuned CNNs with 14 crops per test image and predictions adjusted to new class priors, which has an accuracy of 60.3%.

1. **Deep Residual Learning for Image Recognition** [5]

In this paper, the authors utilize deeper neural networks with an innovative approach that facilitates the training of networks that are deeper than those used previously. Adding more layers to an ANN can give way to problems: vanishing/exploding gradients, degradation, etc. Instead of hoping each few stacked layers directly fit a desired underlying mapping, the authors explicitly let these layers fit a residual mapping and formulate the mathematical underlying theory to assess this.

The ImageNEt Classification Dataset is used to test their framework. ImageNet 2012 classification dataset that consists of 1000 classes. The models are trained on the 1.28 million training images, evaluated on the 50k validation images, and obtained a result on the test images achieving a lower error in some cases compared with the state-of-the-art algorithms for the same dataset.

1. **Identification of Edible and Non-Edible Mushroom Through Convolution Neural Network**[6]

In this paper, the authors build an image categorization system that classifies mushrooms as edible or not edible applying CNN with several different categories such as LeNEt, AlexNet, etc

The analysis is performed in two stages: the first one consists of applying different classification algorithms. The second one different CCNN architectures are compared. The best accuracy is obtained with DCNN with an accuracy of 93%.

1. **Mushroom Image Recognition using Convolutional Neural Network and Transfer Learning**[7]

This paper also uses a CNN to build an automated mushroom image recognition system. The authors use a dataset of ~1500 images of 38 species of mushrooms, collected using image crawling.[8] The dataset size here and in other papers is significantly smaller than our potential data sources, indicating we may need to trim ours down in some regard to making the computation times more manageable.

This work carried out a comparison experiment using AlexNET, VGGNet, and GoogleNET and achieved 82.63% top-1 accuracy and 96.84% top-5 accuracy.

1. **A Study on CNN Transfer Learning for Image Classification**[9]

This investigation on Convolutional Neural Networks (CNN) addressed several aspects of Machine Learning and determined the usability of this technique by conducting a series of tests to different datasets. The authors propose the use of TensorFlow to retrain a pre-trained Inception-v3 model to learning new features. It was established that Transfer Learning improves the accuracy of a CNN and that we can obtain a significantly better accuracy by increasing the number of epochs and quantity of images in a dataset. The results show that the higher quality and variety of images also help to achieve better results. The findings of this paper provide a solid basis to advance the use of Transfer Learning in deep neural networks. The CNN model, in particular, can be used and refined to achieve more complex models and accurate results.

1. **A New Deep Learning Model for the Classification of Poisonous and Edible Mushrooms Based on Improved AlexNet Convolutional Neural Network** [10]

This research compared the time and accuracy of three pre-trained models: AlexNet, ResNet-50, and GoogLeNet. The authors suggest that a model can be trained using sample data, and its accuracy is dependent on the sample size. Following this rationale, data augmentation was utilized to avoid overfitting and ensure the accuracy of the model. The proposed model to mushroom classification experiments using CNN was found to reduce the duration required for training and testing, while retaining a level of accuracy of 98.5%.

1. **Mushroom Image Classification with CNNs: a Case-Study of Different Learning Strategies**[11]

This study investigates the performance of EfficientNet. A filtering tool was implemented to differentiate full-shape mushroom images from the initial dataset. Using ImageNet, the authors built a custom classifier by modifying the default EfficientNet-B0 model. Several modifications were investigated, including different EfficientNet variants (B0 and B5), initial weights and methodologies of transfer learning. Transfer learning with gradual problem size growths, EfficientNet variant B5 and noisy student initial weights obtained the highest accuracy (92.6%).

1. Data Sources

* 2018 FGVCx Fungi Classification Challenge[12]
  + This dataset contains over 100,000 fungi images, sponsored by the Svampe Atlas [13], containing a comprehensive representation of close to 1500 species of fungi, crowd-sourced from the Danish general public.
* Mushroom Observer[14]
  + This website contains a large glossary of fungi information and images to help recognize the various species of mushrooms.

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