Image Recognition Software for a Web App

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Introduction

- We developed a free food-finding app during HackMT, where users could donate food by filling in relevant information about the food they are offering.
- Previously, the food donor had to manually fill this information every time they hosted food, which became tedious.
- To eliminate the form filling process, we decided to create image recognition for the app using convolutional neural networks.

Methods: Mathematical Executions

- ➔ A common issue when creating neural networks, is the amount of time it takes to train neural networks.
- ➔ We used Rectified Linear Units (ReLU) as our activation function for a few of the hidden layers in our CNN, which can be represented by the equation.
- ➔ Because of its simplicity in computations, we were able to achieve a faster training time for our neural network.

$$f(x) = \max(0, x)$$

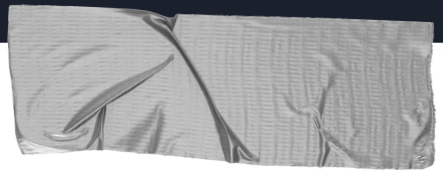
where x is an input value

Methods: Practical Execution

- In the first attempt, we developed a model using the pretrain model MobileNet as our simple base net.
- On a small dataset, the accuracy was good, but when we implemented it with the entire dataset, it did not give us good results.
- Then we tried a couple of MobileNet models such as MobileNetV2 and NASNetMobile.
- The reason that we stick to a Mobile network is that it’s very resource consuming to train a whole massive Imagenet model.

Methods: Model Architecture

- Modern image recognition can require heavy amounts of memory and processing power. Additionally, the training of these neural networks requires large amounts of data.
- To solve this issue, for our models, we used Keras's ImageDataGenerator.
- The data generator provides methods for image pre-processing, such as resizing images, normalizing pixel values, and augmenting the dataset with transformations such as translation or rotation.
- This reduced the strain on the system from trying to load what could be thousands or hundreds of thousands of images all at once.



Results

- ➔ Due to Model 1's 22% accuracy as top 1, Models 2 and 3 had to be created.
- ➔ Although Models 2 and 3 have a higher accuracy than Model 1, it was still not identifying most of the food images.
- ➔ Since Model 1 could identify most of the images within the top 5 and 10, we deployed Model 1 into the Web app.

TABLE I
ACCURACY OF OUR MODELS, AVERAGED OVER 5 FOLDS

	Classes	Top 1	Top 5	Top 10
Model 1	101	22.23%	42.31%	52.56%
Model 2	50	34.30%	59.52%	70.99%
Model 3	25	41.37%	69.17%	80.68%

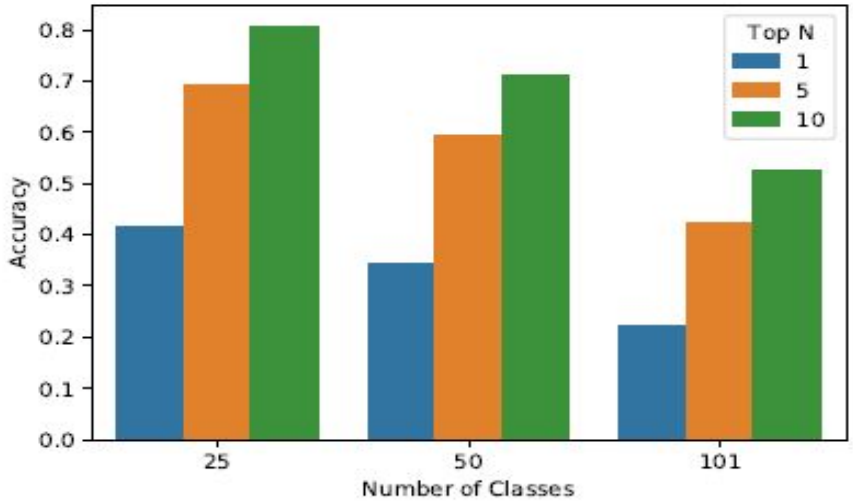


Fig. 2. Top N accuracy values across all 3 models

Implementing Image Recognition

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