1. Definition

1.1. Project Overview

There are several annotated and researched image datasets such as ImageNet, CIFAR-10, and CIFAR100. These datasets have contributed significantly to the field of computer vision (CV). CV is and can be used in several areas, one of which is helping individuals with vision impairment. In this area specifically, identifying cats, dog breeds, and airplanes is useful, however, more focus should be placed on safely navigating indoors, especially in unfamiliar environments. This is one of the encouragements for the launch of MCIndoor20000 dataset, a dataset which consists of indoor objects images. For this project, MCIndoor20000 will be used to develop an algorithm that inputs image path of indoor objects (door, sign, and stairs) and returns the label.

The MCIndoor20000 dataset contains a collection of 2D-RGB images grouped based on three classifications: door, sign, and stairs. Also, MCIndoor20000 contains five additional datasets that were generated via augmentation of the original images using the following techniques:

- 250 window sized Gaussian noise with standard deviation of 10
- 250 window sized Gaussian noise with standard deviation of 20
- Poisson noise
- Salt-pepper noise with density of 0.015
- Rotations

For this project, the original dataset along with Poisson and Gaussian (10) were used. The dataset is publicly available at https://github.com/bircatmcri/MCIndoor20000

1.2. Problem Statement

The dataset intra-class variation is major; however, all the pictures were taken from a single facility, which may lead to generalization challenges. The objective is to develop a convolutional neural network that is able to classify input images into one of three categories: door, sign, and stairs. The model needs to be generalized and able to handle wide spectrum of intra-class variations including images outside of the dataset.

The approach involves setting up the programming environment. Then data Ingestion, exploration, and preparation. Following that, model development and evaluation. Finally, wrapping up the model in a friendlier algorithm.

1.3. Metrics

Data will be split into training, validation, and testing. Training and validation data will be used for training the model, meanwhile, testing will be used to evaluate its performance by calculating the categorical accuracy. A qualitative measure will also be used to assess the model, by testing it on external images with that vary significantly from MCIndoor20000 data.

Given that the problem at hand is prediction of multiple categories, and the categories are relatively balanced and equally important, categorical accuracy will be used. Categorical accuracy is calculated by dividing the number of correct predictions over the total number of predictions as follows:

$$Acc = \frac{\sum_i^n TP_i}{\sum_i^n P_i + N_i}$$

$\boldsymbol{n}: number\ of\ classes$

$\boldsymbol{TP_i}: True\ Positives\ for\ class\ i$

$\boldsymbol{P_i}: Positives\ for\ class\ i$

$\boldsymbol{N_i}: Negatives\ for\ class\ i$

2. Analysis

2.1. Data Exploration and Visualization

Please refer to section 1.1 of this report for information on the input data. The ingested data consists of 6166 images distributed as follows:

- Total number of Door images: 2262
- Total number of Sign images: 2106
- Total number of Stairs images: 1798
-

The images are not of constant size and shape. The sizes and shapes are mixed in the original dataset. However, they were all converted to a standard shape and size as discussed in the following sections. No abnormalities are observed in the dataset.

Sample from the dataset:

Figure 1. Sample images from each class

As shown in the sample, image sizes are large making it impractical to load the dataset into memory for training. Also, different images have different sizes. Another observation is the intraclass variations in terms of colors, angle, shape, and aspect ratio.

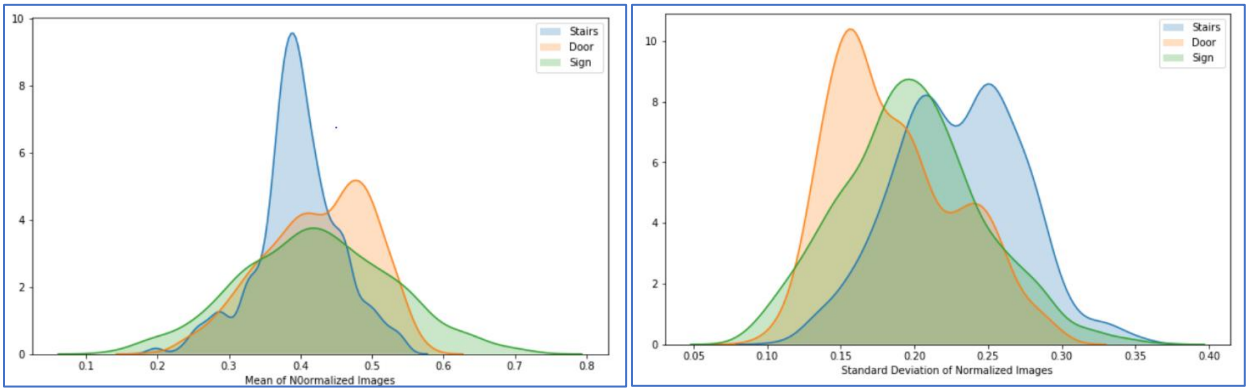


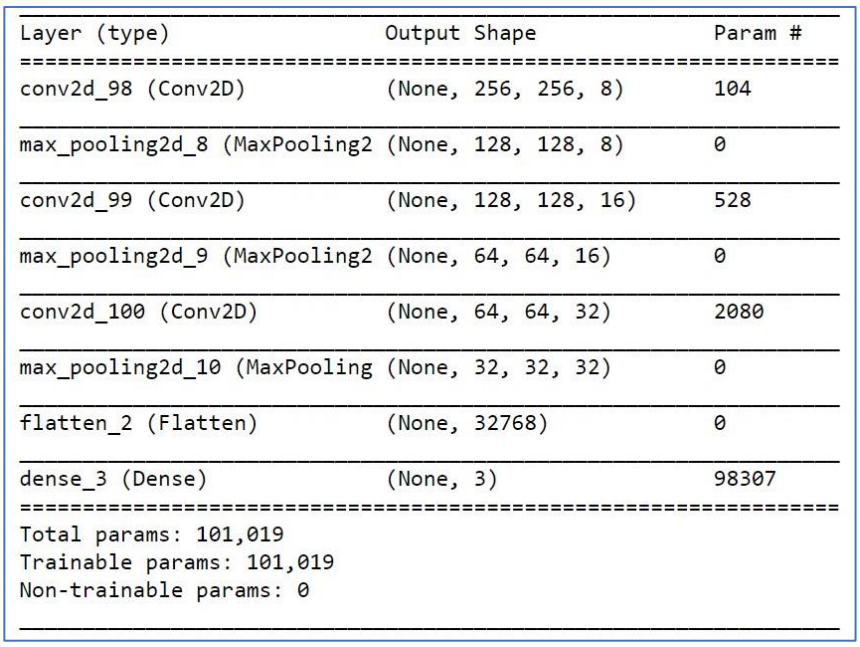
Figure 2. Mean of normalized images (left) and standard deviation of normalized images (right)

Upon examining the pixel intensity mean (Fig. 2 Left)) across images, it can be noted that **Sign** class images mean have the widest distribution, which is expected given that it is the class with highest variations. Additionally, by looking at the distribution of the standard deviation (Fig. 2 Right) across images, **Stairs** class exhibits the highest standard deviation (high contrast between steps, steps shadow, and walls), meanwhile, **Doors** exhibits the lowest standard deviation (doors normally plain one color).

2.2. Algorithms and Techniques

Convolutional Neural Networks

Convolution neural networks (CNNs) use three main types of layers: convolutional layer, pooling layer, and fully-connected layer. Convolutional layers help in feature extraction via applying weight matrix (window) filters over the image. Pooling layers reduce the spatial size by defining a moving window and only returning the max or average values. As depth increase more features are extracted via convolutional layers and spatial dimensions (heights/width) are reduced via pooling layers. Finally, fully connected layers are used to input the extracted features and generate a classification. Refer to figure 3 for an example of a CNN architecture.



Layer (type)	Output Shape	Param #
conv2d_98 (Conv2D)	(None, 256, 256, 8)	104
max_pooling2d_8 (MaxPooling2	(None, 128, 128, 8)	0
conv2d_99 (Conv2D)	(None, 128, 128, 16)	528
max_pooling2d_9 (MaxPooling2	(None, 64, 64, 16)	0
conv2d_100 (Conv2D)	(None, 64, 64, 32)	2080
max_pooling2d_10 (MaxPooling	(None, 32, 32, 32)	0
flatten_2 (Flatten)	(None, 32768)	0
dense_3 (Dense)	(None, 3)	98307

Total params: 101,019
Trainable params: 101,019
Non-trainable params: 0

Figure 3. Architecture for CNN from scratch

Transfer Learning:

Another method for model development is via transfer learning. This is achieved by utilizing the weights of a pre-trained model. For example, InceptionV3 with frozen weights was used in this project without the top layers. Then a trainable global average pooling and a dense layer with softmax activation were added for classification. This technique utilizes the feature extraction of pre-trained models, which enables the development of new models with high performance even when the dataset sample size is relatively small.

2.3. Benchmark

The intended benchmark was the model from scratch. However, given that the dataset is small, the model achieved a very high categorical accuracy (98.5%). Overfitting is suspected and noticed when external images are used. However, it is difficult to benchmark on external images since a large number needs to be collected and labeled first.

For these reasons, the CNN from scratch model will be used for benchmarking qualitative generalization, meanwhile, a deep neural network was used to establish the accuracy baseline. The neural network achieved an accuracy of 35%. Please refer to Fig. 4 for neural network architecture.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 256, 256, 50)      200
_________________________________________________________________
dense_5 (Dense)              (None, 256, 256, 50)      2550
_________________________________________________________________
flatten_1 (Flatten)          (None, 3276800)           0
_________________________________________________________________
dense_6 (Dense)              (None, 3)                 9830403
=================================================================
Total params: 9,833,153
Trainable params: 9,833,153
Non-trainable params: 0
```

Figure 4. Baseline neural network architecture

3. Methodology

3.1. Data Preprocessing

Given the large size of images, they had to be reprocessed to a standard smaller size. The script for resizing them is titled `resize_images.py`. They were resized to (256,256, 3)/(299,299,3) sizes. The images were also split into training (81%), validation (9%), and testing (10%).

3.2. Implementation

Process Metrics & Techniques:

- All images were resized to a standard (256,256,3) / (299,299,3) sizes
    - Used library *imageio.imread* for reading the images
    - *scipy.misc.imresize* to resize the images
    - *imageio.imsave* to save the images
    - *multiprocessing* for threading the script for speedup purposes

- Data was split into training (81%), validation (9%), and testing (10%)
    - Used *sklearn.model_selection.train_test_split* twice to get the three splits

- Target values (class) were converted to dummy variables
    - Used *keras.utils.np_utils* convert flat classification array to dummy categorical array.

- (nb, 256, 256, 3) tensors were created where nb is the number of samples
    - Read images from paths using *imageio.imread*
    - Used *numpy.expand_dims* to convert (256, 256, 3) to (1, 256, 256, 3) shape
    - Used *numpy.vstack* to stack images to form the shape (nb, 256, 256, 3)

- Tensors normalized by dividing over 256

The following steps utilized *keras* library

- Built CNN architecture as follows:
    - Inception_v3 without top layer
    - Global average pooling layer
    - Dense output layer with softmax activation and three nodes

- Compiled CNN architecture with following parameters:
    - Optimizer: 'rmsprop',
    - Loss: 'categorical_crossentropy',
    - Metrics: ['accuracy', 'categorical_accuracy']

- Developed model utilizing training and validation data with following parameters:
    - Epochs: 3
    - Batch Size: 20

- Evaluated on test data

- Evaluated on small sample size of external images

Complications:

- One of the complications faced initially was how to input a non-relational dataset into the python environment from a filesystem, while maintain the labels. Upon research, a useful tool was identified that ingest that returns all images data-paths with labels being the names of sub-directories. The tool is *sklearn.datasets.load_files.*
- Another complication was overloading the device memory. This occurred upon attempting to load the dataset into the environment. For solving that, a script was developed to load, resize, and save all images one at a time. Refer to the process section for details.

3.3. Refinement

First, convolutional neural network was developed from scratch. It consisted of three layers of conv/pooling for feature extraction via narrowing down width/height and increasing depth. Finally, for classification, a flatten and dense layer were included. This resulted in ~100k total number of parameters. Given the size of the dataset, overfitting is a concern. Given that the dataset is small, the model achieved a very high categorical accuracy (98.5%). Overfitting is suspected and noticed when external images are used. However, it is difficult to benchmark on external images since a large number needs to be collected and labeled first.

For these reasons, the CNN from scratch model was used only for benchmarking qualitative generalization, meanwhile, a deep neural network was developed to establish the accuracy baseline. The neural network achieved an accuracy of 35%. Please refer to Fig. 4 for neural network architecture.

Finally, InceptionV3 was used without the top layer and froze all the weights. Then a trainable global average pooling and a dense layer with softmax activation were added for classification. The model achieved high accuracy (98.3%) and did well on external small dataset.

One of the questions that may come to mind is "**Why InceptionV3**." The main driver of this last activity is to overcome the issue of over-fitting given the small size of the dataset. The objective is to use transfer learning for generalizing the classification model. The selection of InceptionV3 is due to the allure of its complexity. Nonetheless, as noted in the improvement section, a less complex model may deliver the same results and be faster in terms of training and fitting.

4. Results

4.1. Model Evaluation and Validation

The final model was test on small sample size of external and correctly classified every image. As for categorical accuracy it achieved 98.3% accuracy on MCIndoor20000 testing test, and 100% on the external small testing set.

4.2. Justification

Qualitative assessment of the final model reveals it generalized better than the benchmark model (35%). High accuracy is achieved (98.3%), with good generalization. With some improvements (see improvements section) the model should be ready for beta testing.

To verify the robustness of the model, a 5-Fold cross validation was conducted on it. The results of the experiments is listed in Figure 5.

	Categorical_Accuracy
1	0.968421
2	0.976499
3	0.991071
4	0.958604
5	0.970779
mean	0.973075
std	0.011958

Figure 5. Results of 5-Fold cross-validation

5. Conclusion

5.1. Free Form Visualization

Testing the model on external dataset

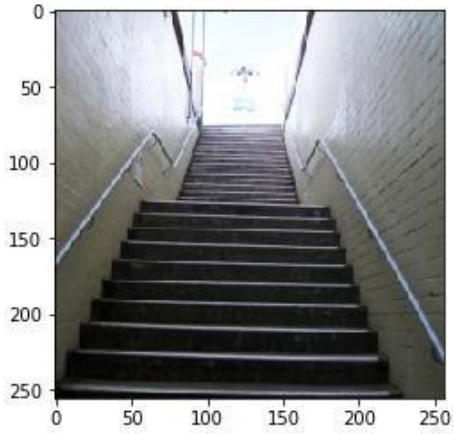
```
Detecting ...
Door detected ahead of you!
```


```
Detecting ...
Sign detected ahead of you!
```


```
Detecting ...
Sign detected ahead of you!
```


```
Detecting ...
Stairs detected ahead of you!
```

```
Detecting ...
Sign detected ahead of you!
```




```
Detecting ...
Sign detected ahead of you!
```


```
Detecting ...
Door detected ahead of you!
```

5.2. Reflection

Going through this project has helped reinforce the concepts of implementing convolutional neural networks. Identifying the problem to be tackled and a relevant dataset was a challenge of its own. After identifying the problem and dataset, the workflow of this project can be outlined as follows

- Setting up a cloud computing and storing environment.
    - Researched different cloud services and became familiar with the concepts
    - Started a GCP account and set up a virtual machine (VM)
    - Prepared the environment using only the command line
    - Configured firewall-settings & Jupyter notebook to be able to connect remotely
- Data Ingestion
    - Downloaded the data into the VM
    - Had to further configure the environment to unzip the files
    - Resized the images to be able to load them into the memory
        - Developed a stand-alone script to easily configure it
        - Learned how to implement threading in python to speed up the process given the large number of images (utilize CPU and overcome disk delays)
- Image data representation
    - Set up some functions to convert image paths to 4D tensors accepted by TensorFlow
- Baseline model development (benchmark model)
- From scratch model development
- Model development using transfer learning
- Verifying model performance using KFold cross validation

Overall, going through this project has help me reinforce the concepts of implementing convolutional neural networks. Also, the more challenging aspect was handling images as input into the python environment. It motivated me to learn more about image representation.

5.3. Improvements

There are few limitations and some improvements ideas that can be addressed in future iterations

- A classification for non-stair/door/sign images (perhaps enforce a softmax threshold?)
- Testing the model on larger labeled external dataset to ensure generalizability
- Developing a web interface (via flask) for accessing the model
- Testing various starting transfer learning algorithms to identify the one that is simplest, yet deliver high accuracy and generalizability
- Utilize cloud computing with GPU to improve speed