A picture containing text, clipart

Description automatically generated

*School of Computing*

|  |  |
| --- | --- |
| Student Name | Sakthignana Sundaram Somaskandan |
| Student Number | 14346091 |
| Email Address | Sakthignana.somaskandan2@mail.dcu.ie |
| Program of Study | M.Sc. in Computing (Part-time) |
| Programme Code | MCM |
| Project Title | Computer Vision Assignment 22/23 |
| Module code | EE544 Computer Vision |
| Module Coordinator | Prof. Paul F. Whelan |
| Project Due Date | 22nd March 2023 |

|  |
| --- |
| *I/We declare that this material, which I/we now submit for assessment, is entirely my own work and has not been taken from the work of others, save and to the extent that such work has been cited and acknowledged within the text of my work. I/We understand that plagiarism, collusion, and copying are grave and serious offences in the university and accept the penalties that would be imposed should I engage in plagiarism, collusion or copying. I/We have read and understood the Assignment Regulations. I/We have identified and included the source of all facts, ideas, opinions, and viewpoints of other in the assignment references. Direct quotations from books, journal articles, internet sources, module text, or any other source whatsoever are acknowledged, and the sources cited are identified in the assignment references. This assignment, or any part of it, has not been previously submitted by me/us or any other person for assessment on this or any other course of study.*  *I/We have read and understood the referencing guidelines found at* [*http://www.dcu.ie/info/regulations/plagiarism.shtml*](http://www.dcu.ie/info/regulations/plagiarism.shtml)*,* [*https://www4.dcu.ie/students/az/plagiarism*](https://www4.dcu.ie/students/az/plagiarism) *and/or recommended in the assignment guidelines* |

Name: *Sakthignana Sundaram Somaskandan* Date: *22nd March 2023*

Table of Contents

[Introduction 4](#_Toc130148310)

[Multi-class image classification 4](#_Toc130148311)

[Dog breed classification using fine-tuning based transfer learning 4](#_Toc130148312)

[Techniques 4](#_Toc130148313)

[Artificial Neural Network 4](#_Toc130148314)

[Activation function 5](#_Toc130148315)

[Loss function 5](#_Toc130148316)

[Optimisation function 5](#_Toc130148317)

[Backpropagation 5](#_Toc130148318)

[Convolutional Neural Network (CNN) 5](#_Toc130148319)

[Convolution 6](#_Toc130148320)

[Max pooling 6](#_Toc130148321)

[Flattening 6](#_Toc130148322)

[Dropout 6](#_Toc130148323)

[Dense layer 6](#_Toc130148324)

[Transfer Learning 6](#_Toc130148325)

[Design 7](#_Toc130148326)

[Multi-class image classification 7](#_Toc130148327)

[Data Split 7](#_Toc130148328)

[Model Architecture 7](#_Toc130148329)

[Dog breed classification using fine-tuning based transfer learning 9](#_Toc130148330)

[Model Architecture 9](#_Toc130148331)

[Implementation 9](#_Toc130148332)

[Multi-class image classification 9](#_Toc130148333)

[Step 1: Prepare the dataset 9](#_Toc130148334)

[Step 2: Split the data into train, test and validation 10](#_Toc130148335)

[Step 3: Define model architecture 10](#_Toc130148336)

[Step 4: Fit the model on the train set 11](#_Toc130148337)

[Step 5: Evaluate the model on the test set 12](#_Toc130148338)

[Dog breed classification using fine-tuning based transfer learning 12](#_Toc130148339)

[Step 1: Prepare the dataset 12](#_Toc130148340)

[Step 3: Define model architecture 13](#_Toc130148341)

[Testing, Results & Analysis 13](#_Toc130148342)

[Multi-class image classification 13](#_Toc130148343)

[Sample Data 13](#_Toc130148344)

[Baseline 14](#_Toc130148345)

[Experiment 1: Data Split 14](#_Toc130148346)

[Experiment 2: Dropout with early stopping 15](#_Toc130148347)

[Experiment 3: Data Augmentation 15](#_Toc130148348)

[Experiment 4: L2 Regularisation 16](#_Toc130148349)

[Testing 16](#_Toc130148350)

[Dog breed classification using fine-tuning based transfer learning 16](#_Toc130148351)

[Sample Data 16](#_Toc130148352)

[Testing 17](#_Toc130148353)

[Discussion & Conclusion 17](#_Toc130148354)

[Multi-class image classification 17](#_Toc130148355)

[Dog breed classification using fine-tuning based transfer learning 18](#_Toc130148356)

[GitHub Repo Link 18](#_Toc130148357)

[References 18](#_Toc130148358)

[Appendix 18](#_Toc130148359)

General requirements:

1. Best practise is to use the third person passive voice
2. Audience: write the report so that your peers will understand it
3. Font use Times New Roman 12 point or similar
4. There is no page quantity requirement
5. Address all the questions/issues raised in the assignment sheet as these form the basis of your mark
6. Report is evaluated based on the clarity and communication of the ideas involved.
7. All quantitative results, including the test procedures used to evaluate the effectiveness of the method chosen should be included in the report.
8. A key element of this assignment is your ability to design and implement your own test strategy where required.

# Introduction

To the specific task. Context – briefly describe the overall aims and objectives of the task.

The assignment consists of two parts:

1. Multi-class image classification – training from scratch using ImageNette.
2. Dog breed classification using fine-tuning based transfer learning.

## Multi-class image classification

ImageNette is a subset of 10 easily classified classes from the ImageNet dataset: tench, English springer, cassette player, chain saw, church, French horn, garbage truck, gas pump, golf ball, and parachute. The dataset has a train/validation split of 1000/500 images per class. The objective of the task is to design, implement and experiment with ways to improve the baseline performance of a *vgglite* network implemented from scratch using the Keras library [1].

## Dog breed classification using fine-tuning based transfer learning

ImageWoof contains 10 dog classes from the ImageNet dataset: Australian terrier, Border terrier, Samoyed, Beagle, Shih-Tzu, English foxhound, Rhodesian ridgeback, Dingo, Golden retriever, Old English sheepdog. The dataset has a train/validation split of 1300/50 images. This task aims to implement transfer learning and fine-tune the ResNet50 model using the Keras library.

# Techniques

Explain the approach adopted and why.

## Artificial Neural Network

Artificial neural networks (ANN) are inspired by neural activity in biology. The human brain is composed of cells called neurons that exchange signals with one another, forming a very dense and complex network. ANNs are simpler than the neural networks in the brain, but they share a couple of key components in the architecture. The similarities are depicted in Figure 1. Each node can have many inputs with only one output. A neural network comprises of layers of nodes, where each layer communicates with the subsequent layer.

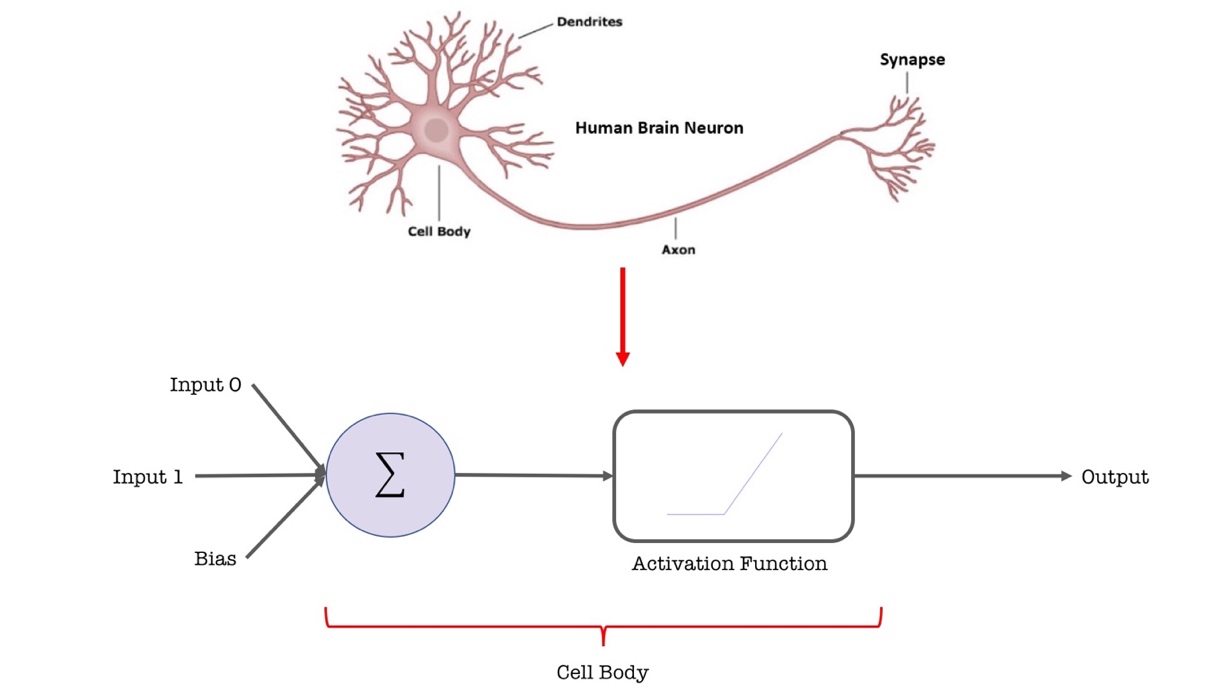


Figure 1: Biological Neuron v Artificial Neuron

## Activation function

Activation functions are non-linear functions applied to the summed product of weights and biases of a neuron. This is what enables a neural network to learn a non-linear mapping of the data. There are several different activation functions: sigmoid, tanh and relu.

## Loss function

Loss functions are used to quantify the error in the output. It is the difference between the true and the predicted output. The objective of the model is to minimise this measure. There are several different loss functions: cross entropy.

## Optimisation function

Optimisation functions are used to update the model parameters (weights and biases) so that the loss function diminishes over epochs. Optimisation functions can be constant learning rate algorithms and adaptive learning rate algorithms. There are several different optimisation functions: rmsprop, adam.

## Backpropagation

Backpropagation refers to the feedback process in a neural network after a batch of data is processed. The algorithm updates every parameter in the network depending on its influence on the loss function. The main goal of this process is to find weights and biases that result in the smallest possible error value. The chain rule is used to analytically compute the partial derivatives that are the gradient of the error. For this reason, functions used in a neural network are required to be differentiable.

## Convolutional Neural Network (CNN)

Convolutional Neural Networks are also inspired by neurobiology, specifically the visual cortex which processes data only for its local receptive field.

### Convolution

Convolution is a technique that slides a kernel across the image and computes the sum of products of each element of the kernel with the corresponding element in the sub-matrix of the image. The process of convolution can be represented mathematically as:

The size of the output image after convolution is determined by: the size of the input image, the size of the kernel, the stride and the padding. The kernel size defines the field of view of the convolution. The stride refers to the number of steps the kernel takes after each iteration of the convolution process. Each convolution process results in only one output pixel value. Therefore, bigger the stride the smaller the output. Padding is a technique to handle the border of an image in an attempt to retain valid edge pixels.

### Max pooling

Pooling is a process of downsampling the input to reduce the computational load and the risk of overfitting. The output size of a pooling layer depends on the strides between the pools. Max pooling is among many other techniques where the maximum value within the pooling window is taken and discards the rest. There are no trainable parameters in a pooling layer. The risk of losing valuable information during this process could impact the model's performance.

### Flattening

Flattening is a process of converting a multi-dimensional vector to a one-dimensional vector before passing the extracted features to the classifier.

### Dropout

The concept behind dropout is to randomly deactivate a specified percentage of the neurons in the network during training to address the overfitting issue.

### Dense layer

A dense layer, also called a fully connected layer, essentially refers to the number of connections a layer has to its subsequent layer. The neurons in a dense layer are connected to every neuron in the subsequent layer and hence do not have a local receptive field like a convolutional layer.

## Transfer Learning

Transfer learning is the process of fine-tuning a model for a task that is different to the task on which the model was originally trained. The hyperparameters of a network are saved and stored so that they can be reused for a different task. The advantage of this technique is that an industry-leading model can be trained on a very large dataset, and this model can then be repurposed for a specific task by simply training the last dense layers. Essentially, the idea is to use the pre-trained model as a feature extractor. For this to work, the layers must be left untouched by the new model during training, also known as the freezing of layers.

# Design

Detailed outline for solution – see course notes for details on using pseudo code descriptions.

## Multi-class image classification

The system's design to classify images involves using CNNs and Dense layers with activation, loss and optimisation functions to aid learning. The activation, loss and optimisation functions are carefully chosen for the task and the type of images present in the dataset.

### Data Split

The data is split into training, validation and test sets. The training set is used to train the model parameters. The validation set is used to fine-tune the model parameters, and the test set is used to evaluate the model on unseen data. The main premise of splitting the data into equally distributed sets is to train and evaluate the model’s performance. The ratio of the split depends on the amount of data available. The split ratio used for this task is broken down in Table 1.

Table 1: Data Split Information

|  |  |  |  |
| --- | --- | --- | --- |
| ImageNette | Train | Validation | Test |
| Ratio | 70 | 20 | 10 |
| Samples |  |  |  |

### Model Architecture

The model architecture of a CNN network is depicted in Figure 2.

Schematic

Description automatically generated with medium confidence

Figure 2: vgglite CNN network

The input is an image from the ImageNette dataset. The image gets processing the following stage:

1. The first convolutional layer with 32 filters and a filter size of extracts relevant features from the input and outputs a feature map. Each filter in the layer detects a different feature.
2. The second convolutional layer with 32 filters and a filter size of takes the feature map from the first convolutional layer and applies more filters to relevant more abstract features.
3. The feature map from the second convolutional layer then gets down sampled by the pooling layer with a pooling size of where the maximum value over an input window is taken.
4. The above three steps are repeated once again with 64 filters and filter size of for the convolutional layers and down sampled one more time with max pooling with pool size of . The aim of this process is to pass only the decisive information to the fully connected (Dense) layer.
5. The three-dimensional image data gets flattened to a one-dimensional vector prior to the dense layer.
6. The dense layer captures the flattened vector and outputs the probability of the input image belonging to each class using the *softmax* activation function.

Conv2D layers use the following default parameters:

The model is trained on the training dataset for a specified number of epochs and batch size. The batch size refers to the number of samples that propagate through the network at any one time during training.

The objective of the network is to converge and learn a good mapping function that represents the data. In terms of the activation function, ReLU is chosen due to the advantages of computational efficiency and sparse activated network. The loss function chosen is cross entropy. The optimisation function chosen is Adam due to its ability of variable learning rate.

A summary of the model workflow is illustrated in Figure 3.

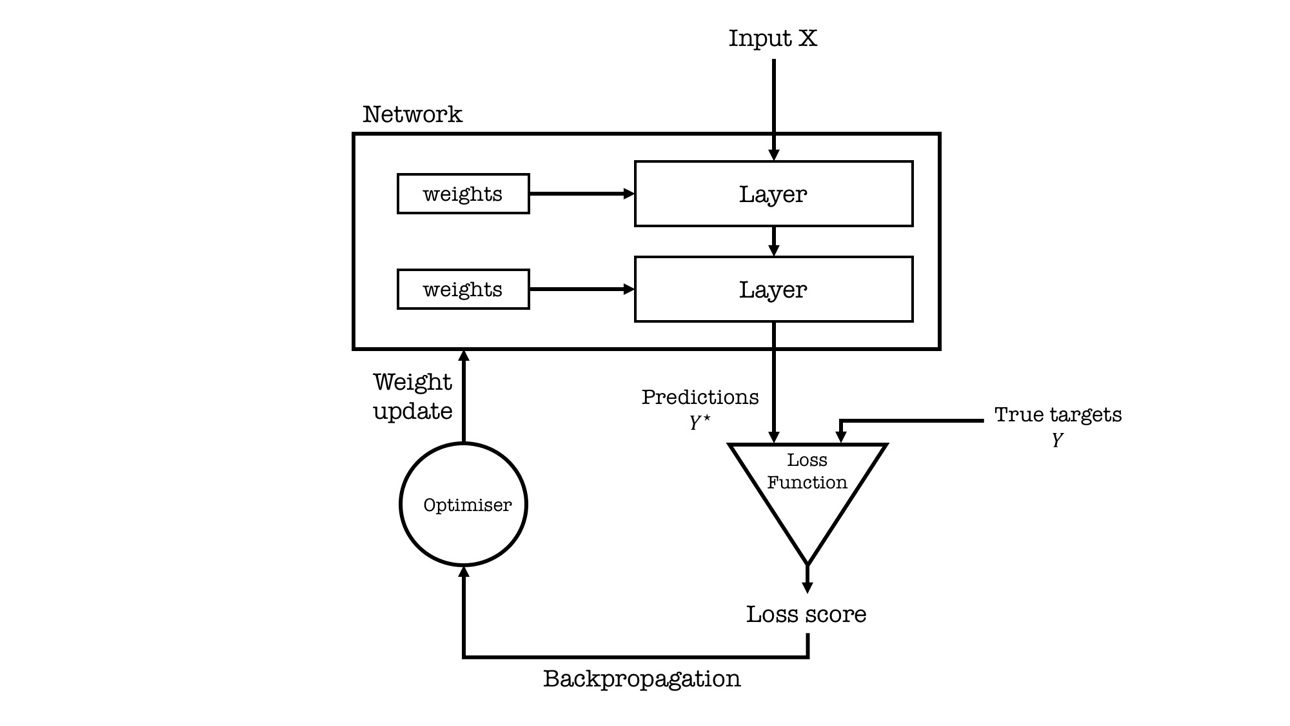


Figure 3: Network workflow

## Dog breed classification using fine-tuning based transfer learning

The system's design to classify images for this task involves using the transfer learning technique. The concept of transfer learning is depicted in Figure 4.

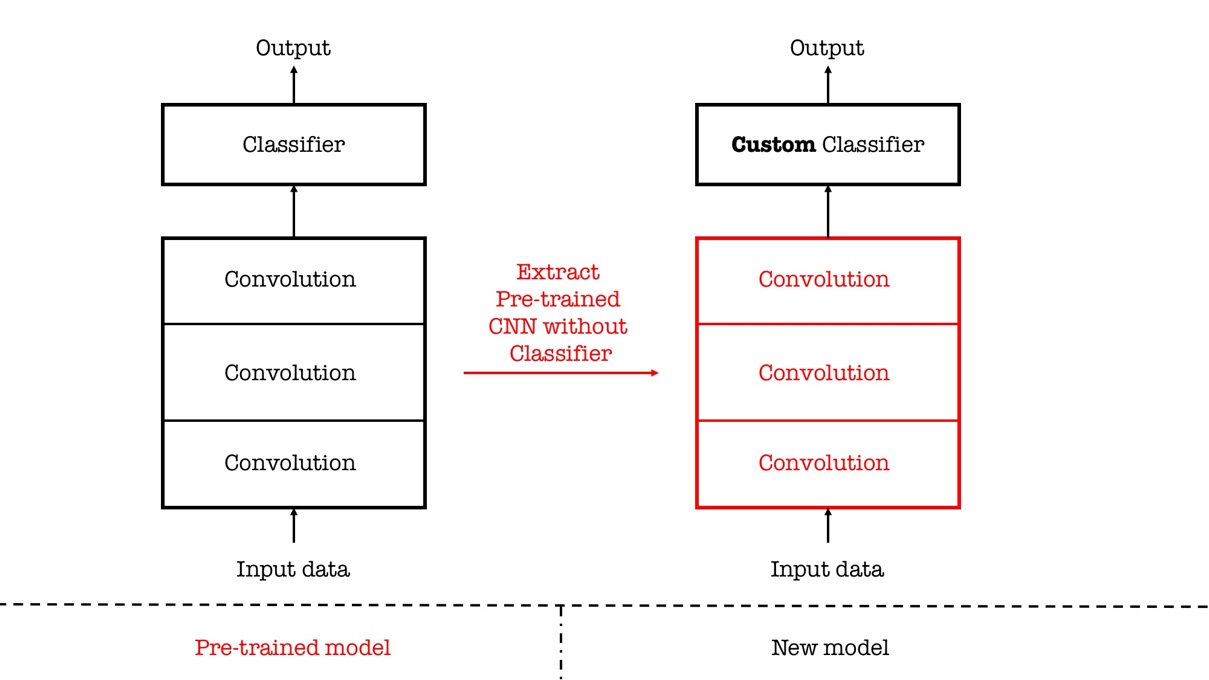


Figure 4: Concept of transfer learning

### Model Architecture

The model architecture consists of the pre-trained ResNet50 model and a custom classifier on top of the ResNet50 model. The first 141 layers of the model are frozen, which means the pre-trained weights are frozen and not fine-tuned. The last 33 layers (res5c block) are unfrozen so that it can be fine-tuned. The model is fine-tuned on the ImageWoof dataset to be able to classify images of different dog breeds present in the dataset. The ResNet50 model takes an input of shape where three refers to the number of channels present in the image data.

# Implementation

Key aspects, example of your implementation details – reference relevant sections of your full code listing in the appendix as appropriate.

The full code listing can be found in the Appendix section.

## Multi-class image classification

### Step 1: Prepare the dataset

The dataset was downloaded from [here](https://s3.amazonaws.com/fast-ai-imageclas/imagenette2-160.tgz). Since the dataset contains ten classes, this assignment requires picking four classes as the working dataset. The following four classes were picked:

1. n03445777 – golf ball
2. n03417042 – garbage truck
3. n02979186 – cassette player
4. n03028079 – church

|  |
| --- |
| def load\_dataset(img\_folder):  for dir in os.listdir(img\_folder):  if dir == 'n03445777' or dir == 'n03417042' or dir == 'n02979186' or dir == 'n03028079' :  for file in os.listdir(os.path.join(img\_folder, dir)):  image\_path = os.path.join(img\_folder, dir, file)  image = tf.keras.preprocessing.image.load\_img(image\_path, target\_size=(IMG\_WIDTH,IMG\_HEIGHT))  image = np.array(image)  data.append(image)  labels.append(dir)  load\_dataset(PATH\_TO\_TRAIN\_DATA)  load\_dataset(PATH\_TO\_VAL\_DATA) |

Once the classes were selected, the images corresponding to the selected classes had to be loaded into the program to manipulate the data further. The load\_img function from the Keras library was used to read the images given the image\_path (the zip file containing the data was uploaded to Google Drive and unzipped using the tar command in Colab) and the target size of the images. The target size is as the input layer of the model is expected to be an image of size , where three refers to the number of channels (RGB – colour image).

### Step 2: Split the data into train, test and validation

The data was split using the train\_test\_split function from the scikit-learn library, which takes image array, label array, test set size, and the random state as inputs [2]. The random state is for the reproducibility of the output sets. Furthermore, the class distribution of each dataset is also visualised in Colab, as it is a good practice to maintain the same distribution among the datasets for effective model performance.

|  |
| --- |
| X\_train, X\_test, y\_train, y\_test = train\_test\_split(data, labels, test\_size=0.30, random\_state=42)  X\_val, X\_test, y\_val, y\_test = train\_test\_split(X\_test, y\_test, test\_size=0.33, random\_state=42) |

This is a multi-class image classification problem where the model output is the probability value of an input image belonging to each class. To enable this, the labels of the dataset must be one hot encoded representing the true class of an image.

|  |
| --- |
| def one\_hot\_encode(y, num\_classes):  le = LabelEncoder()  return to\_categorical(le.fit\_transform(y), num\_classes) |

### Step 3: Define model architecture

### The model architecture outlined in the assignment sheet has been translated to code using the Keras library functions: Conv2D, MaxPooling2D, Flatten, Dense, and various other functions were used to define and compile the model, as seen below. The build\_model function definition takes a few additional parameters to enable experimentation of the model to enhance its performance. The results obtained by running the model can be seen in Step 1: Prepare the dataset

The dataset is prepared the same way, but the dataset is different, and hence the classes picked are also different:

1. n02105641 – Shih-Tzu
2. n02087394 – Beagle
3. n02096294 – English foxhound

Additionally, the target size is which is what the ResNet50 model expects to take as input.

### Step 3: Define model architecture

The ResNet50 model is fetched using the Keras function API with the top of the model excluded and weights associated with the ImageNet dataset. Once the ResNet50 model is obtained, the initial 143 layers are frozen by setting the trainable parameter to False. The custom classifier is defined afterwards using Dense and GlobalAveragePooling2D layers.

|  |
| --- |
|  |

Once the model is defined, it is trained, and results are visualised. The results can be seen in the Testing, Results & Analysis section.

Testing, Results & Analysis section.

|  |
| --- |
| def build\_model(batchNorm=False, dropOut=False, l2Reg=False):  model = Sequential()  if l2Reg:  model.add(Conv2D(32, kernel\_size=3, activation='relu', kernel\_regularizer='l2', input\_shape=(64,64,3)))  model.add(Conv2D(32, kernel\_size=3, activation='relu', kernel\_regularizer='l2'))  else:  model.add(Conv2D(32, kernel\_size=3, activation='relu', input\_shape=(64,64,3)))  model.add(Conv2D(32, kernel\_size=3, activation='relu'))    model.add(MaxPooling2D(pool\_size=(2,2)))  if batchNorm:  model.add(BatchNormalization())  if l2Reg:  model.add(Conv2D(64, kernel\_size=3, activation='relu', kernel\_regularizer='l2'))  model.add(Conv2D(64, kernel\_size=3, activation='relu', kernel\_regularizer='l2'))  else:  model.add(Conv2D(64, kernel\_size=3, activation='relu'))  model.add(Conv2D(64, kernel\_size=3, activation='relu'))    model.add(MaxPooling2D(pool\_size=(2,2)))  if batchNorm:  model.add(BatchNormalization())  model.add(Flatten())  if l2Reg:  model.add(Dense(512, kernel\_regularizer='l2'))  else:  model.add(Dense(512))    if dropOut:  model.add(Dropout(0.25))  if l2Reg:  model.add(Dense(NUM\_CLASSES, activation='softmax', kernel\_regularizer='l2'))  else:  model.add(Dense(NUM\_CLASSES, activation='softmax'))  model.compile(  optimizer=Adam(),  loss='categorical\_crossentropy',  metrics=[  CategoricalAccuracy(),  Precision(),  Recall(),  AUC()  ]  )  return model |

### Step 4: Fit the model on the train set

Once the model architecture was defined, the model was fit using the training and validation datasets for 30 epochs. A couple of callback functions were defined to enable EarlyStopping and save ModelCheckpoint. The checkpoint callback function was used to save the best model weights monitoring the val\_categorical\_accuracy.

|  |
| --- |
| early\_stopping = EarlyStopping(monitor='val\_loss', verbose=1, patience=20)  checkpoint = ModelCheckpoint('/content/drive/MyDrive/EE544 Computer Vision/task-1-weights.hdf5', verbose=1, save\_best\_only=True, monitor='val\_categorical\_accuracy')  baseline\_history = baseline\_model.fit(  train\_ds,  epochs=30,  verbose=1,  validation\_data=val\_ds,  callbacks=[checkpoint]  ) |

The datasets used for model fitting were prepared using the ImageDataGenerator function in the Keras library. This was done to rescale the image and optionally add data augmentation techniques to the training dataset.

|  |
| --- |
| train\_datagen = ImageDataGenerator(  rescale=1./255,  fill\_mode="nearest"  )  val\_datagen = ImageDataGenerator(rescale=1./255)  test\_datagen = ImageDataGenerator(rescale=1./255)  train\_ds = train\_datagen.flow(  np.array(X\_train), y\_train,  shuffle=True,  batch\_size=128  )  val\_ds = val\_datagen.flow(  np.array(X\_val), y\_val,  shuffle=True,  batch\_size=128  )  test\_ds = test\_datagen.flow(  np.array(X\_test), y\_test,  shuffle=False,  batch\_size=128  ) |

### Step 5: Evaluate the model on the test set

### The evaluation of the model was done on the trained model. The following functions were defined to streamline the evaluation process for the various experiments conducted. The results obtained from executing these functions can be seen in Step 1: Prepare the dataset

The dataset is prepared the same way, but the dataset is different, and hence the classes picked are also different:

1. n02105641 – Shih-Tzu
2. n02087394 – Beagle
3. n02096294 – English foxhound

Additionally, the target size is which is what the ResNet50 model expects to take as input.

### Step 3: Define model architecture

The ResNet50 model is fetched using the Keras function API with the top of the model excluded and weights associated with the ImageNet dataset. Once the ResNet50 model is obtained, the initial 143 layers are frozen by setting the trainable parameter to False. The custom classifier is defined afterwards using Dense and GlobalAveragePooling2D layers.

|  |
| --- |
|  |

Once the model is defined, it is trained, and results are visualised. The results can be seen in the Testing, Results & Analysis section.

Testing, Results & Analysis section.

|  |
| --- |
| def plot(train, validation, ylabel, title):  plt.plot(train, color='red', label='train')  plt.plot(validation, color='blue', label='validation')  plt.title(title)  plt.ylabel(ylabel)  plt.xlabel('Epoch')  plt.legend()  plt.grid(linestyle='-', linewidth=0.5)  def evaluate\_and\_predict(model):  # evaluate on test dataset  eval\_results = model.evaluate(test\_ds, batch\_size=30)  # print evaluation results  print('Test loss:', eval\_results[0])  print('Test categorical\_accuracy:', eval\_results[1])  print('Test precision:', eval\_results[2])  print('Test recall:', eval\_results[3])  print('Test auc:', eval\_results[4])  # predict  return model.predict(test\_ds)  def draw\_confusion\_matrix(true, pred):  cm = confusion\_matrix(true.argmax(axis=1), pred.argmax(axis=1))  sns.heatmap(cm, annot=True, annot\_kws={"size": 12}, fmt='g', cbar=False, cmap="viridis")  plt.show()  print(classification\_report(y\_test.argmax(axis=1), pred.argmax(axis=1))) |

## Dog breed classification using fine-tuning based transfer learning

The steps involved in this task are mostly the same as the above task, except for a few changes:

### Step 1: Prepare the dataset

The dataset is prepared the same way, but the dataset is different, and hence the classes picked are also different:

1. n02105641 – Shih-Tzu
2. n02087394 – Beagle
3. n02096294 – English foxhound

Additionally, the target size is which is what the ResNet50 model expects to take as input.

### Step 3: Define model architecture

The ResNet50 model is fetched using the Keras function API with the top of the model excluded and weights associated with the ImageNet dataset. Once the ResNet50 model is obtained, the initial 143 layers are frozen by setting the trainable parameter to False. The custom classifier is defined afterwards using Dense and GlobalAveragePooling2D layers.

|  |
| --- |
|  |

Once the model is defined, it is trained, and results are visualised. The results can be seen in the Testing, Results & Analysis section.

# Testing, Results & Analysis

Include sample data and use tables and/or sample images/diagrams to illustrate your points as appropriate.

## Multi-class image classification

### Sample Data

|  |  |
| --- | --- |
| Class | Image |
| Golf ball | A picture containing grass, athletic game, sport, golf  Description automatically generated |
| Garbage truck | A picture containing text, truck, building, outdoor  Description automatically generated |
| Cassette player | A picture containing text, indoor, stereo, appliance  Description automatically generated |
| Church | A white building with a red door  Description automatically generated with low confidence |

### Baseline

|  |  |  |  |
| --- | --- | --- | --- |
| Test Loss | Test Accuracy | Train Loss | Train Accuracy |
| 1.3349 | 0.8112 |  |  |

|  |  |
| --- | --- |
| Confusion Matrix | Classification Report |
|  |  |

### Experiment 1: Data Split

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Split | Test Loss | Test Accuracy | Train Loss | Train Accuracy |
| 80/10/10 | 1.4147 | 0.7889 |  |  |
| 60/30/10 | 1.4135 | 0.7722 |  |  |
| 70/20/10 | 1.3286 | 0.8262 |  |  |

### Experiment 2: Dropout with early stopping

|  |  |  |  |
| --- | --- | --- | --- |
| Test Loss | Test Accuracy | Train Loss | Train Accuracy |
| 0.5268 | 0.8262 |  |  |

|  |  |
| --- | --- |
| Confusion Matrix | Classification Report |
|  |  |

### Experiment 3: Data Augmentation

|  |  |  |  |
| --- | --- | --- | --- |
| Test Loss | Test Accuracy | Train Loss | Train Accuracy |
| 1.4107 | 0.7813 |  |  |

|  |  |
| --- | --- |
| Confusion Matrix | Classification Report |
|  |  |

### Experiment 4: L2 Regularisation

|  |  |  |  |
| --- | --- | --- | --- |
| Test Loss | Test Accuracy | Train Loss | Train Accuracy |
| 0.7754 | 0.8206 |  |  |

|  |  |
| --- | --- |
| Confusion Matrix | Classification Report |
|  |  |

### Testing

## Dog breed classification using fine-tuning based transfer learning

### Sample Data

|  |  |
| --- | --- |
| Class | Image |
| Shih-Tzu |  |
| Beagle | A picture containing dog, sitting, brown, indoor  Description automatically generated |
| English foxhound | A dog running on grass  Description automatically generated with medium confidence |

### Testing

# Discussion & Conclusion

## Multi-class image classification

Since the baseline model architecture overfitted the data after approximately seven epochs, a few experiments were conducted to overcome the overfitting problem. The following techniques were explored [3]:

1. Dropout with early stopping
2. Data Augmentation
3. L2 Regularisation

Dropout is a regularisation technique that prevents overfitting. Dropout randomly drops the specified percentage of neurons from the network during training. When neurons in the network are randomly dropped, it’s equivalent to training different networks. The net effect of different overfit neural networks is to reduce overfitting. Using dropout reduced overfitting with the help of early stopping.

Data augmentation refers to applying augmentation techniques to the dataset: flipping, translation, scaling, adding noise etc. This helps add more variety to the dataset and reduce overfitting by forcing the model to generalise. Though data augmentation didn’t fully avoid overfitting, it took more epochs to overfit.

L2 regularisation adds a penalty to the loss function and aims to minimise the squared magnitude of the weights. L2 regularisation was chosen to overcome overfitting because it can learn complex data patterns, and image data is usually considered complex data to be modelled. This is clear in the loss and accuracy plots where the overfitting is solved and provides good data modelling.

## Dog breed classification using fine-tuning based transfer learning

Not a summary – refer back to the problem and give insight into the impact of your solution on addressing this task. Discuss key outcomes, e.g., is it what is expected clearly detailing your reasoning, issues that arose as part of your implementation.

# GitHub Repo Link

# References

[1] “Keras: Deep Learning for humans.” https://keras.io/ (accessed Mar. 19, 2023).

[2] “scikit-learn: machine learning in Python — scikit-learn 1.2.2 documentation.” https://scikit-learn.org/stable/index.html (accessed Mar. 19, 2023).

[3] A. Sagar, “5 Techniques to Prevent Overfitting in Neural Networks - KDnuggets,” *KD Nuggets*, 2019. https://www.kdnuggets.com/2019/12/5-techniques-prevent-overfitting-neural-networks.html (accessed Mar. 19, 2023).

# Appendix

Full code listing for each section, e.g., your Jupyter notebook (please comment your code appropriately). Large amount of numerical data if generated. Include all relevant material that would otherwise interrupt the flow of the main report.