Prediction of different types of blood cells using Convolutional Neural Network

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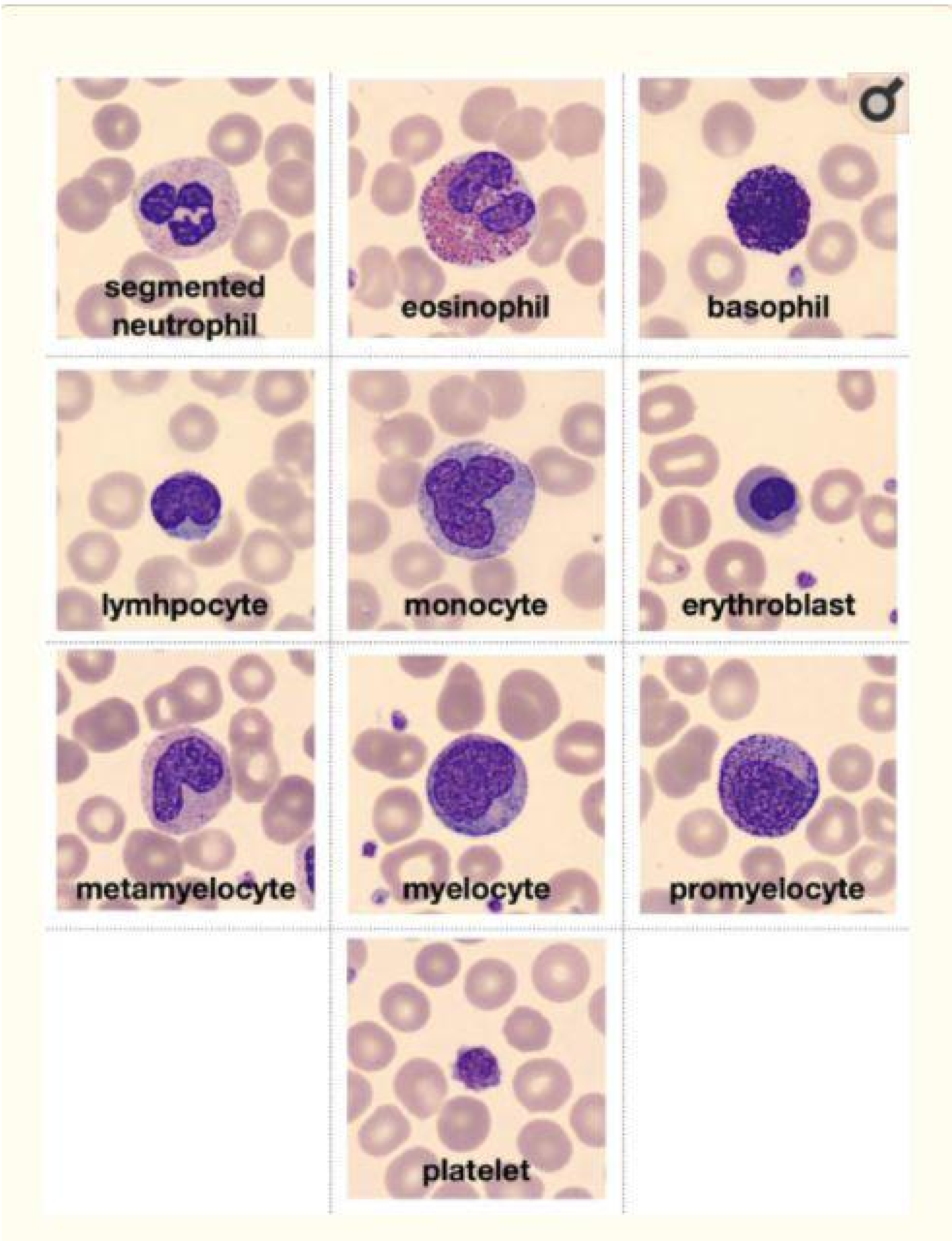
Contents

Dataset:

The dataset provided consisted of thousands of blood cell images. They were acquired in the Core Laboratory at the Hospital Clinic of Barcelona. For these blood cell images, samples were obtained from individuals without any infection or having any sort of disease. These images were of high quality and can be downloaded directly from ' https://data.mendeley.com/public-files/datasets/snkd93bnjr/files/2fc38728-2ae7-4a62-a857-032af82334c3/file_downloaded ' . A brief review is given below. For more details, visit ' https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7182702/ ' .

- Total Number of Images: 17092
- Total Number of classes/labels: 8
    1. Basophil: 1218 images (7.13%)
    2. Eosinophil: 3117 images (18.24%)
    3. Erythroblast: 1551 images (9.07%)
    4. Immature Granulocytes: (labeled as 'ig') consist of further three types: metamyelocytes, myelocytes and promyelocytes. These are considered as single class and have total of 1420 images (8.31%)
    5. Lymphocyte: 1214 images (7.10%)
    6. Monocyte: 1420 images (8.31%)
    7. Neutrophil: 3329 images (19.48%)
    8. Platelet: 2348 images (13.74%)
- Example Images of each class:

- 

- Image Properties:
    - RGB image
    - Format: “jpg”
    - Size: (360, 363)

When using this dataset for training the model, images were preprocessed as follows:

- Dataset was split in ratio (60 : 20 : 20) as (training, validation, test) dataset.
- Mean Image of the training dataset was calculated and was used for zero centering of the dataset.
- Due to limited computational resources, Images were scaled down to size (50, 50)
- Images were mapped between 0 and 1 by dividing it with 255.
- Images obtained from dataset had a shape of (width, height, channels). Since the code used the convention as (channels, width, heights), they were reshaped to match the convention.

- Although, images were annotated with whole numbers (1-8) representing class but throughout the program, they were manipulated such that as if they were one hot encoded.
- It was found that there is one hidden image in ‘ Neutrophil ’ folder which was removed. This was apart from 17092 images.
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Architecture Components:

The code makes use of classes extensively for writing each component required in the architecture of the CNNs. The implementation is such that it makes the program very flexible and different type of layers can easily be added by simply following a template. Consequently, the code itself contains number of parts but the report discusses only those components which were used in the training of the model.

Dataset:

This is a class in CNN_Training_Code.ipynb’ which is responsible for reading images, for preprocessing them and for splitting the dataset. The essence of this class is that rather than loading all the images in the memory at the same time, it keeps paths to images in memory and using them, load images whenever required. Details are as follows:

- The constructor takes following arguments:
    - ‘path’: path to the folder consisting of folders of images. This path must of a directory which consist of directories named with labels having their images inside them. This architecture of folders is important as code depends on it.
    - ‘resize’: size in which image needs to be resized (optional)
    - ‘split_ratio’: The ratio in which data needs to be split in. (default = 60,20,20). The splting is achieved through a method ‘ SplitData() ‘.
    - ‘zero_center’: this can take one of the two values:
        - ‘per_channel’ : this calculates mean for each channel (i.e it results in three numbers) over the entire training dataset and uses it for zero centering of the data. This is calculated using method ‘PerChannelMean()’
        - ‘image’ : this calculates mean image across the entire training dataset. It is achieved by method ‘MeanImage()’
- The most important method in this class is ‘load_data()’. This method can be called on the object with a ‘flag’ (specifying ‘train’, ‘valid’ and ‘test’) and ‘batch’ (list with starting and ending index). This will read image, preprocess the image, annotate images with labels (i.e whole numbers) and return batch of images with labels as single numpy array.

Convolutional Layer:

This class performs convolution of weights with images. It performs both forward and backward propagation of the layer with methods ‘forward()’ and ‘backward()’. Details are as follows:

- The constructor takes following arguments:
    - ‘number_of_filters’: number of filters to be convolved with activations.
    - ‘filter_size’: The size of filter (same for both horizontal and vertical direction)
    - ‘stride’ : the size of step to take in either direction (default =1)
    - ‘zero_padding’: number of padding to apply around the activation maps (default=0).
- The combination of filter_size (F), activations (A), zero_padding (P) and stride (S) must be such that it results in whole number for this equation:

$$for\ each\ axis,$$

$$O = \frac{A-F+2P}{S} + 1$$

- The operation of convolution is given by:

$$f[x,y] * g[x,y] = \sum_{n_1=-\infty}^{\infty} \sum_{n_2=-\infty}^{\infty} f[n_1,n_2] \cdot g[x-n_1, y-n_2]$$

- Since this layer has weights associated with it, during backward pass, the derivative with respect to input as well as weights need to be calculated. It was found that derivative w.r.t weights was equal to valid convolution of global gradient with inputs and the derivative w.r.t inputs was equal to full convolution of global gradients with rotated weights.

Activation Function:

There are number of activation function implemented in the code but the ones we are concerned with, are class ‘ LeakyReLU’ and class ‘Softmax’. Just like convolutional layer, these classes have forward and backward methods associated with them:

- ‘LeakyReLU’: This function is used in the hidden layers as a mean to introduce nonlinearity in the model. the constructor allows the user to set the value of slope (‘a’ in the following equation) (default=0.01) and it is given by

$$g(x)=\max(ax, x)$$

And its derivative is given by

$$g'(x) = a \text{ if } x < 0$$
$$g'(x) = 1 \text{ if } x > 0$$

- ‘Softmax’: This function is used as the output layer (last layer) with cross entropy as loss function. It results in probabilities and whose sum is equal to 1. It is given by

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Its derivative is given by

$$\frac{\partial p_j}{\partial o_i} = p_i(1-p_i), \quad i = j$$

$$\frac{\partial p_j}{\partial o_i} = -p_i p_j, \quad i \neq j.$$

It may be noted that the derivative of this layer results in a jacobian matrix but since we are using one hot encoded approach, all terms become zero except the main diagonal which are equal to the first equation above and which depend upon the gradient flowing from the next layer

Pooling Layer:

Just like other layers, this class also has forward and backward methods. Details are below:

- The constructor takes following arguments:
  - 'pooling_type' : The type of pooling that needs to be performed. It can either be 'max', 'average' or 'global'. (The latter two are implemented but not discussed as they were not used in model)
  - 'filter_size': The size of filter (same for both horizontal and vertical direction)
  - 'stride' : the size of step to take in either direction (default =1)
  - 'zero_padding': number of padding to apply around the activation maps.
- The combination of filter_size (F), activations (A), zero_padding (P) and stride (S) must be such that it results in whole number for the following equation:

$$for\ each\ axis,$$

$$O = \frac{A-F+2P}{S} + 1$$

- The max pooling involves slides a square window of filter_size over the activation map and outputs the highest value inside the window. On the other hand, during back propagation, global gradients flow only on values where highest value existed (for all other values, it is zero)

Fully Connected Layer:

This class also has forward and backward functions.

- The constructor takes 'neurons' for this layer as parameter.
- It performs linear function to the previous layer activations to get an output:

$$y = x * w + b$$

- As this layer has weights associated with it, the derivatives are as follows:
  - $dW =$ transpose(x) * GlobalGrad
  - $dX = GlobalGrad * transpose(t)$

Cross Entropy Loss Layer:

This class calculates cross entropy loss using the results of softmax function.

- The constructor takes 'number of classes' as argument which is used to make sure that the last layer has the same number of neurons as that of classes.
- The operation results in log likelihood of the output class. For loss, we want to minimize this value. It is given by:

$$\boxed{L_i = -\log P(Y = y_i | X = x_i)}$$

It may be noted that natural log was used in calculation. And during the backward pass of layer, the gradient is given below and flows only to the node of actual class:

$$L^{'} = \frac{1}{x}$$

-

Evaluation Metrics:

In order the evaluate the model, two different evaluation metrics were used:

- ‘ClassAccu’: This takes the output of softmax layer and actual labels and tells the number of correctly predicted classes.
- ‘ConfMatrix’: This also takes the same input, but it calculates confusion matrix which is later used for calculation of precision, recall and F1 score:

$$Precision\ (P)\ =\ \frac{TP}{TP+FP}$$

$$Recall\ (R)\ =\ \frac{TP}{TP+FN}$$

$$F1\ Score\ =\ \frac{2*P*R}{P+R}$$

Optimizers:

To update the parameters, a methodology is required. The program has number of methods implemented but the one which was used for training is ‘AD’ (Adam) optimizer. This technique updates the weights using the following technique:

$$m_t = \beta_1 * m_{t-1} + (1-\beta_1) * \nabla w_t$$

$$v_t = \beta_2 * v_{t-1} + (1-\beta_2) * (\nabla w_t)^2$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \qquad \hat{v}_t = \frac{v_t}{1-\beta_2^t}$$

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} * \hat{m}_t$$

Furthermore, it uses L2 regularization

Network:

This is the class that is the runner function. With the help of number of helper functions, it carries out weight initialization, forward propagation, back propagation, gradient checking, and training of the network. However, the user is only supposed to create an object of the class and call the method ‘train’ on it. Everything is taken care off. A brief overview is given below:

- The constructor takes number of arguments:
  - ‘layers’: This is the list of class objects that defines the architecture of CNN. For a network with two convolution layers, two pooling layers and two fully connted layer with ReLU as activation function and Cross entropy as Loss function, this would look like as

    [Conv, ReLU, Pool, Conv, ReLU, Pool, FC, ReLU, FC, Softmax, CELoss]
  - ‘weights_init’ and ‘bias_init’: this defines how to initializer parameters in the network. It can take constant values or one of the methods: ‘Gauss’ (with specified mean and standard deviation as arguments), ‘Xavier’ (Gauss distribution with mean = 0 and std = 1/sqrt(number of input neurons) or ‘He’ (Gauss distribution with mean

=0 and std = 1/sqrt(number of input neurons/2). The number of input neurons for Convolutional layer is calculated as follows: (filter_size*filter_size*channels)
  - 'optimizer': object of one of the optimizer class which will be used for updating parameters
  - 'eval_metric': this is optional but can specified as list of class objects of evaluation metrics which will be used for evaluation of model.

- To make sure the derivatives calculated analytically are correct, this class also exposes a function 'gradeint_check' which calculates derivatives numerically. This operation is computationally expensive that is why the runner function which controls it, limits it to run only for single iteration. It has a dictionary which stores all original weights and derivatives of the network and calculated derivatives and prints them at the end for confirmation that derivatives calculated analytically are correct. It uses the following formula for each parameter:

$$\frac{dJ}{dw} = \frac{J(w+e)-J(w-e)}{2*e}$$

- In order to train the network, method 'train()' is exposed. This takes number of arguments:
  - 'data': object of the class 'Dataset'
  - 'train_batch_size': this is number of the examples after which weights are updated
  - 'valid_batch_size': since images are in large number, validation data is loaded in batches and is evaluated on loss function and error metrics
  - 'epochs': Number of times the complete training dataset needs to be passed through the network
  - 'lr': Learning rate
  - 'lmbda': Regularization Parameter
  - 'grad_check': whether to calculate gradient numerically or not

  This method calls method 'load_data' on 'Dataset' object to obtain batch of images, after that it carries out forward propagation and calculates loss and accuracy using evaluation metrics. Afterwards, the model is evaluated on validation data. And, finally, it updates parameters of the function.

Model:

The architecture of the CNN is as follows:

1. Convolutional Layer:
   - Number of Filters = 4
   - Filter Size = 11
   - Stride = 1
   - Zero Padding = 1
   - Number of Parameters = 1456

2. Leaky ReLU Activation Function:
   - Slope = 0.01

3. Pooling Layer:
   - Type = max

- Filter Size = 2
- Stride = 2
- Zero Padding = 0

4. Convolutional Layer:
    - Number of Filters = 8
    - Filter Size = 3
    - Stride = 1
    - Zero Padding = 1
    - Number of Parameters = 296

5. Leaky ReLU Activation Function:
    - Slope =0.01

6. Pooling Layer:
    - Type = max
    - Filter Size = 3
    - Stride = 2
    - Zero Padding = 0

7. Fully Connected Layer:
    - Neurons = 200
    - Number of Parameters: 160200

8. Leaky ReLU Activation Function:
    - Slope = 0.01

9. Fully Connected Layer:
    - Neurons = 8
    - Number of Parameters = 1608

10. Softmax Activation Function

11. Cross Entropy Loss
    - Number of Classes = 8

Total number of parameters in the network = 163560

Visual depiction of the Weights associated with Convolutional Layers are available in Annex B.

Objective Function:

The objective function or cost function which is used for optimizing the parameters is as follows:

$$J(w) = \frac{1}{m}\left[\sum_{k=1}^{m} \frac{e^{s_{y_i}}}{\sum_j e^{s_j}} + \frac{\lambda}{2}\sum_{j=1}^{n} w_j^2\right]$$

$$where\ m = number\ of\ training\ examples$$
$$n = number\ of\ parameters$$
$$\lambda = regularization\ parameter$$

Adam optimizer is used for optimization of weights. Furthermore, for evaluation the following functions are used:

$$J(w) = \frac{1}{m}\left[\sum_{i=1}^{m} \frac{e^{s_k}}{\sum_j e^{s_j}}\right]$$

$$Classification\ Accuracy\ = \frac{Number\ of\ Correctly\ Classified\ Examples}{Total\ Number\ of\ Examples}\ x\ 100$$

$$Precision\ (P)\ = \frac{TP}{TP+FP}$$

$$Recall\ (R)\ = \frac{TP}{TP+FN}$$

$$F1\ Score\ = \frac{2*P*R}{P+R}$$

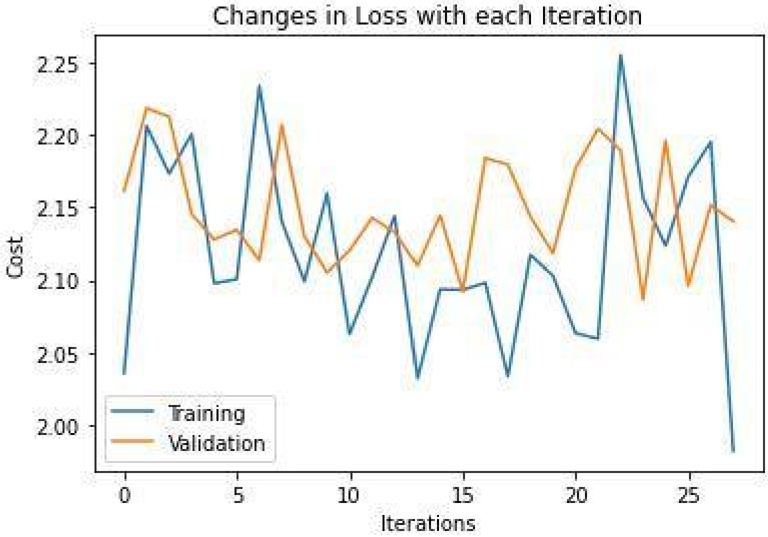
Hyperparameters:

Hyperparameters of the model were set as follows:

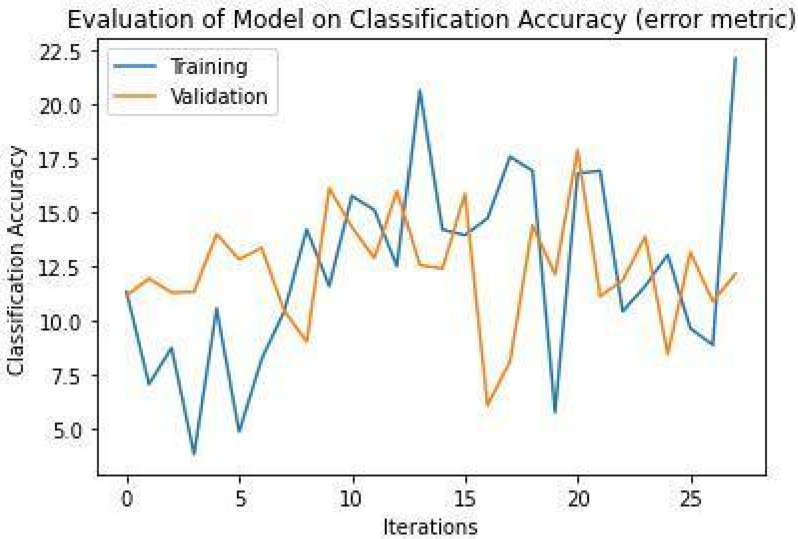
- Weights' initialization = He
- Bias initialization = 0.01
- Optimizer = Adam (beta1 = 0.9, beta2 = 0.999)
- L2 Regularization
- Regularization Parameter = 0.001
- Learning Rate = 0.0001
- Epochs = 2
- Train batch size =768
- Valid batch size =1024

Plotting:

The following plot shows how training and validation cost changes over the time (or with each iteration).



The following plot shows Classification Accuracy for training and validation dataset changes over time



Saving Model for Future Use:

Some of the model as well as dataset properties are needed for the prediction code and thus these values are stored in special numpy format(.npy). The values saved are:

- Resizing of Image
- Mean of Image
- Name of Classes
- Name of Layers in ordered form
- Parameters of layers

Error Metric on Train, Valid and Test Data:

A function 'calculate_error' is defined for calculation of loss, classification accuracy, confusion matrix and F1 score for each score for each dataset:

Training Dataset:

```
The total cost on  train  data is  2.137111176845495
The Classification Accuracy on  train  data is  13.651877133105803
```

	basophil	eosinophil	erythroblast	ig	lymphocyte	monocyte	neutrophil	platelet
basophil	39.0	60.0	31.0	80.0	40.0	36.0	81.0	18.0
eosinophil	93.0	259.0	108.0	237.0	87.0	109.0	237.0	185.0
erythroblast	168.0	421.0	185.0	405.0	149.0	218.0	419.0	275.0
ig	129.0	344.0	156.0	299.0	138.0	151.0	414.0	266.0
lymphocyte	60.0	163.0	96.0	120.0	80.0	47.0	132.0	160.0
monocyte	96.0	295.0	109.0	247.0	90.0	139.0	269.0	204.0
neutrophil	48.0	120.0	45.0	134.0	52.0	59.0	130.0	24.0
platelet	86.0	242.0	187.0	204.0	88.0	89.0	334.0	269.0

	Precision	Recall	F1 score
basophil	0.101299	0.054242	0.070652
eosinophil	0.196958	0.136029	0.160920
erythroblast	0.082589	0.201745	0.117200
ig	0.157617	0.173233	0.165057
lymphocyte	0.093240	0.110497	0.101138
monocyte	0.095928	0.163915	0.121027
neutrophil	0.212418	0.064484	0.098935
platelet	0.179453	0.192006	0.185517

Validation Dataset:

```
The total cost on  valid  data is  2.2302133645028017
The Classification Accuracy on  valid  data is  16.530134581626683
```

	basophil	eosinophil	erythroblast	ig	lymphocyte	monocyte	neutrophil	platelet
basophil	30.0	97.0	49.0	93.0	27.0	40.0	80.0	70.0
eosinophil	20.0	24.0	16.0	34.0	15.0	10.0	31.0	28.0
erythroblast	33.0	106.0	50.0	108.0	46.0	57.0	105.0	83.0
ig	37.0	79.0	32.0	76.0	25.0	27.0	69.0	54.0
lymphocyte	10.0	12.0	10.0	11.0	6.0	7.0	13.0	6.0
monocyte	17.0	76.0	25.0	56.0	27.0	30.0	87.0	30.0
neutrophil	105.0	259.0	111.0	208.0	92.0	112.0	302.0	192.0
platelet	7.0	16.0	12.0	20.0	8.0	9.0	10.0	47.0

	Precision	Recall	F1 score
basophil	0.061728	0.115830	0.080537
eosinophil	0.134831	0.035874	0.056671
erythroblast	0.085034	0.163934	0.111982
ig	0.190476	0.125413	0.151244
lymphocyte	0.080000	0.024390	0.037383
monocyte	0.086207	0.102740	0.093750
neutrophil	0.218682	0.433286	0.290664
platelet	0.364341	0.092157	0.147105

Test Dataset:

```
The total cost on  test  data is  2.2272426677608013
The Classification Accuracy on  test  data is  11.085112606025154

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:62: RuntimeWarning: invalid value encountered in double_scalars
```

	basophil	eosinophil	erythroblast	ig	lymphocyte	monocyte	neutrophil	platelet
basophil	58.0	94.0	43.0	95.0	31.0	37.0	94.0	39.0
eosinophil	24.0	60.0	44.0	57.0	23.0	30.0	71.0	68.0
erythroblast	107.0	321.0	121.0	287.0	112.0	139.0	306.0	216.0
ig	17.0	57.0	34.0	37.0	20.0	16.0	62.0	70.0
lymphocyte	27.0	72.0	34.0	75.0	33.0	31.0	102.0	66.0
monocyte	0.0	0.0	0.0	0.0	0.0	0.0	1.0	4.0
neutrophil	25.0	54.0	23.0	51.0	18.0	32.0	52.0	29.0
platelet	1.0	11.0	6.0	4.0	9.0	7.0	9.0	18.0

	Precision	Recall	F1 score
basophil	0.118126	0.223938	0.154667
eosinophil	0.159151	0.089686	0.114723
erythroblast	0.075202	0.396721	0.126437
ig	0.118211	0.061056	0.080522
lymphocyte	0.075000	0.134146	0.096210
monocyte	0.000000	0.000000	NaN
neutrophil	0.183099	0.074605	0.106014
platelet	0.276923	0.035294	0.062609

Prediction Code:

To make predictions on unknown dataset of images, a separate file 'CNN_Prediction_Code.ipynb' is provided. This separates the training code and makes it easier for the user to estimate the outputs on his dataset. This file has a function 'Prediction' which takes one argument:

- 'path' : path to directory containing images on which prediction needs to be made

It stores paths to all images in the folder, and then looks for model "Model.npy" and helper functions file "CNN_Training_Code.py" in the current directory. Afterwards, it loads all the data from model file and imports classes required from helper function file. Then it makes objects of these classes and assigns corresponding values to the layers thereby making the complete network. After that, it reads the images one by one, preprocess it, makes inference, and displays the predicted label for each image with probability. More details on how to run this code is provided in Annex A.

Annexes:

Note: The Code was written using Google Colab and it is thus formatted in that way. Incase you want to re-run using other editor/environment, you would have to adjust the code accordingly to see the outputs or some outputs will not be visible because of the way Jupyter Notebook works. Further, although the complete codes are provided in the annexes, but it is recommended to read the code through .ipynb file. Moreover, both .ipynb and .py files for both Training Code and Prediction Code is provided. However, 'CNN_Training_Code.ipynb' and 'CNN_Training_Code.py' are slightly different as the later was adjusted slightly so that classes required by 'CNN_Prediction_Code.ipynb' could easily be imported.

Annex A: Instructions on running the code

- Open the file 'CNN_Prediction_code.ipynb' in a python environment and place the files named as 'Model.npy' and 'CNN_Training_Code.py' in the same directory as that of .ipynb file.
- Create a folder in the same directory and place all the images on which prediction need to be made. (a test folder is provided for reference)
- In the .ipynb file, run the libraries block and function prediction block. Then call the function by passing the argument:
    - 'path': path to your created folder

  You will see results coming up one by one. A template is available in .ipynb file. You can reuse it by simply changing the directory according to your own requirement.
- Make sure all .ipynb and .py files are in the same directory.
- Image must be of format '.jpg' and of type 'uint8'. If the code doesn't find any image meeting these criterion, it will terminate.

Annex B: Training Code with Optimal Parameters:

Training Code:

```
import numpy as np
import pandas as pd
import os
import sys
from matplotlib import pyplot as plt
from PIL import Image as pilimg
%matplotlib inline

class Dataset:
  '''
    Returns an object of "Dataset" class that is used as input to 'Network'
class.

    Paramters:

      'path' : str
        path to main folder containing subfolders of images in a specific st
ructure. For more info, see notes.

      'resize' : tuple of ints (width, height) (optional)
        shape of image in which it would be resized to. If no value is passe
d, no resizing will be done.

      'split_ratio' : tuple of int or float (train_size_percent, valid_size_
percent, test_size_percent) Default = (60,20,20) (optional)
        ratio in which data will be split. The sum of the values must be equ
al to 100.

      'zero_center': str = 'per_channel' or 'image'. Default = None (optiona
l)
        defines zero centering of the data. It can take one of the folllowin
g values:

            'per_channel' : Subtract the mean per channel calculated over al
l images (like in VGG)
            'image' : Subtract mean image calculated over all images (like i
n AlexNet)

        If no value is passed, zero centering of the data will not be done

    Notes:

      - The class expects images to be in certain architecture of folders. T
here should be one main folder whose path will be passed
        to the parameter 'path'. Inside this main folder, there should be, e
qual to number of classes, folders. Each folder should be named
        with class label and inside it, there should be only images (in jpeg
 format, each having same size with shape(W,H,3)) of this class.
        Make sure there are no hidden folders.Everything else except folders
 and images will be ignored.
```

```
      - The class expects images to be in uint8 format as it will map these
values between 0 and 1 for better processing.

  '''

  def __init__(self, path, resize = None, split_ratio = (60,20,20), zero_cen
ter = None):


    #check whether correct value for 'path' is provided

    if not os.path.isdir(path):
      sys.exit("Invalid Path provided. The path must be a valid directory")

    #store labels
    self.labels = [label for label in os.listdir(path) if os.path.isdir(os.p
ath.join(path, label)) and not label.startswith('.') ]
    self.labels.sort()


    if len(self.labels) == 0:
      sys.exit("The directory provided is either empty or does not follow th
e specified architecture of folders. For more info, see the documentation of
 class 'Dataset'")
    else:

      data =list()

      for index,label in enumerate(self.labels):

        for image in os.listdir(os.path.join(path, label)):

          if image.endswith(".jpg"):

              #store path to images and annotate it with labels
              data.append([os.path.join(path, label, image), index])


    if len(data) == 0:
      sys.exit("The directories inside the specified folder are either empty
 or does not have images in jpg.")


    print("Total ", len(data), " images found with total ", len(self.labels)
, " classes")
    print('labels', self.labels)

    #Resize
    if resize != None and len(resize) != 2:
        sys.exit("Parameter 'resize' can only take two integers as tuple")

    self.resize = resize

    #Splits the dataset
    if len(split_ratio) != 3:
```

```
      sys.exit("Invalid Values provided for parameter 'split_ratio'. It can
take can only three values as tuple (train, valid, test)")

    elif np.sum(split_ratio) != 100:
      sys.exit("Invalid Values provided for parameter 'split_ratio'. train,
valid and test must add up to 100.")

    else:
      self.train_data, self.valid_data, self.test_data = self.SplitData(data
, split_ratio)

    #Calculate values for zero centering of the data
    if zero_center == None:
      self.mean = 0
    elif zero_center == 'per_channel':
      self.mean = self.PerChannelMean()
    elif zero_center == 'image':
      self.mean = self.MeanImage()
    else:
      sys.exit("Invalid Value Provided for parameter 'zero_center'. It can o
nly take None, 'per_channel' or 'image'. ")




  def SplitData(self, data, split_ratio):
    '''
    Splits the dataset and returns training, validation and test dataset, ea
ch as tuple of (data, labels):

    Parameters:

    data: list of shape (total_images, 2) with 'path to image' in its first
axis and 'label' in the second axis
      Dataset which needs to be split.

    'split_ratio' : tuple of int or float (train_size_percent, valid_size_pe
rcent, test_size_percent)
          ratio in which data will be split. The sum of the values must be e
qual to 100.

    '''
    #Shuffle data
    np.random.shuffle(data)

    #Split data
    train_data, valid_data, test_data = np.split(data, [int((split_ratio[0]/
100)*len(data)), int(((split_ratio[0]+split_ratio[1])/100)*len(data))])

    return train_data, valid_data, test_data



  def PerChannelMean(self):
    '''
```

```
    Calculates and returns mean of each channel over training dataset as arr
ay of size 3 [R,G,B] :

    Notes:

      -  It expects image to be in RBG format with shape (width, height, 3)

    '''

    sum=np.array([0.0])

    for img, _ in self.train_data:

      #Read image
      img = pilimg.open(img)

      #Resize image
      if self.resize != None:
        img =img.resize(self.resize)

      img = np.asarray(img)

      #map image between 0 and 1
      img  = img / 255

      #accumulate values
      sum = sum + img

    #return mean along three channels
    return np.sum(sum, axis=(0,1), keepdims=True)/(self.train_data.shape[0]*
sum.shape[0]*sum.shape[1])


  def MeanImage(self):
    '''
    Calculates and returns mean image over training dataset as array of shap
e (M,N,3).

    Notes:

     -  It expects image to be in RBG format with shape (width, height, 3)

    '''
    sum=np.array([0.0])

    for img, _ in self.train_data:

      #Read image
      img = pilimg.open(img)

      #Resize image
      if self.resize != None:
        img =img.resize(self.resize)

      img = np.asarray(img)

      #map image between 0 and 1
```

```
      img = img / 255

      #accumulate values
      sum = sum + img

    #return mean image
    return sum/self.train_data.shape[0]



  def load_data(self, flag, batch):
    '''
    loads and returns a batch of images with labels of the specified dataset
.
    The output returns two things:

        imgBatch: numpy array of images of shape ( batch, channels, rows, co
ls ):
        labelBatch: numpy array of labels of shape (batch, 1)

    Parameters:

      'flag' : str = 'train', 'valid', or 'test'
        Specifies from which dataset to load the images

      'batch': list of integers [start, end]
        loads images from dataset with the specified indexes as start (inclu
sive) and end (not inclusive)

    '''
    #load path of images from the corresponding dataset

    if flag == 'train':
      files = self.train_data[batch[0] : batch[1]]
    elif flag == 'valid':
      files = self.valid_data[batch[0] : batch[1]]
    elif flag == 'test':
      files =self.test_data[batch[0] : batch[1]]
    else:
      sys.exit("Invalid value provided for parameter 'flag'. It can either b
e 'train', 'valid' or 'test'")


    #build batch of images and labels
    for index, data in enumerate(files):

      #Read image
      img = pilimg.open(data[0])

      #Resize image
      if self.resize != None:
        img =img.resize(self.resize)

      img = np.asarray(img)

      #map image between 0 and 1
```

```
        img  = img / 255

        #zero center the data
        img = img - self.mean

        #reshape image to (depth, width, height)
        img = np.array([img[:,:,0],img[:,:,1],img[:,:,2]])


        #for creating batch of images
        if index == 0:
          imgBatch = np.zeros([len(files), img.shape[0], img.shape[1], img.sha
pe[2]] )

          #by filling with value more than total number of labels, it makes su
re
          #that all values are replaced with proper label (as this will be che
cked by loss fnt in case improper value is passed)
          labelBatch = np.full((len(files), 1) , fill_value = len(self.labels)
+1 )

        imgBatch[index] = img

        labelBatch[index] = data[1]


    return imgBatch, labelBatch


class Conv:
  '''
    Returns an object of "Conv" class that is used as Convolution Layer in C
NNs.

    Paramters:

        'number_of_filters' : non-zero, positive, int
          Number of filters that will be convolved with the activation maps

        'filter_size' : non-zero, positive, odd, int
          size of the square filter

        'stride' : non-zero, positive, int. Default=1 (optional)
          size of step to take in horizontal and vertical direction

        'zero_padding' : positive, int. Default=0 (i.e. no zero padding) (op
tional)
          number of rows and columns of zeros that need to be added around t
he activation maps.
            For example, if it is specified to be as 2 and activations has a
 shape of (batch, channels, rows, cols), then
            after zero padding, the new shape of activations will be (batch,
 channels, rows + 4, cols + 4) with zeros above and below, right and left of
 the axis -1 and -2.


    Notes:
```

```
      -   Combination of stride, zero padding, last two axis of both filters
 and activation maps must be
          such that it results an whole number for the following equation:

                 For each axis:
                         O = ( ( R - F + 2P ) / S ) + 1
                 where
                         O = size of output axis
                         R = size of activation map axis
                         F = size of filter
                         P = amount of zero padding
                         S = stride

  '''

  def __init__(self, number_of_filters, filter_size, stride=1, zero_padding=
0 ):


    #Check whether valid values are provided for paramters and store accordi
ngly

    if number_of_filters <= 0 or number_of_filters % 1 != 0:
      sys.exit("Invalid Value provided for parameter 'number_of_filters'. It
 must be non-zero, positive integer.")
    else:
      self.number_of_filters =number_of_filters

    if filter_size <= 0 or filter_size % 1 != 0 or filter_size % 2 == 0:
      sys.exit("Invalid Value provided for parameter 'filter_size'. It must
be non-zero, positive, odd integer")
    else:
      self.filter_size=filter_size

    if stride <= 0 or stride % 1 !=0:
      sys.exit("Invalid Value provided for parameter 'stride'.It must be non
-zero, positive integer.")
    else:
      self.stride = stride

    if zero_padding < 0 or zero_padding  % 1 !=0:
      sys.exit("Invalid Value provided for parameter 'zero_padding'. It must
 be positive integer.")
    else:
      self.zero_padding=zero_padding

    # Variables associated with this layer
    self.weights=np.array([])
    self.dW=np.array([])

    self.bias=np.array([])
    self.dB=np.array([])

    self.inputs = np.array([])
```

```
  def forward(self, activations, train=False):
    '''
      Performs Convolution of each filter with each image and returns the re
sult with shape = (b, d, r, c):

          b = batch (same as 'activations')
          d = channels (same as 'number of filters')
          r, c = Rows and Columns (calculated using the formula described in
 the constructor of the class)

      Parameters:

        'activations' : numpy array of shape (batch, channels, rows, columns
)
          Activation maps which will be convolved with filters

        'train' : bool. Default=False (optional)
          whether training of the layer is being carried out or not
    '''

    if self.weights.shape[0] != self.number_of_filters:
      sys.exit("Error in number of filters. Number of filters with weights d
o not match with number of filters specified")

    if self.bias.shape[0] != self.number_of_filters:
      sys.exit("Error in number of filters. Number of filters with  bias do
not match with number of filters specified")

    if activations.shape[1] != self.weights.shape[1]:
      sys.exit("Depth of activations do not match with depth of filters. Che
ck the channels of activation map and filters")

    if self.bias.shape[1] != 1:
        sys.exit("Invalid Shape of parameter 'bias'. It must be of shape (nu
mber_of_filters,1)")

    if activations.shape[-1] != activations.shape[-2]:
        sys.exit("The rows and columns (i.e axis =-1 and -2) of Activations
must be same for convolution. ")

    if train:
      self.inputs = activations

    #Apply Zero padding

    pw=[[0,0]]*(np.size(activations.shape)-2) + [[self.zero_padding, self.ze
ro_padding]]*2 #list of pad widths for each axis
    activations = np.pad(activations, pw, 'constant', constant_values=0)

    #Convolution
    output_row_col = ((np.array(activations.shape[-2:]) - self.weights.shape
[-2:])/self.stride)+1

    #check whether filter and activations convolve properly
    if any(output_row_col%1 !=0) :
      print('Properties at this layer:')
```

```
      print('\t Layer type = Convolution')
      print('\t Size of Activations (with zero padding) = ', activations.sha
pe )
      print('\t\t\t ( Batch, Channels, Rows, Columns )')
      print('\t Size of Filters = ', self.weights.shape )
      print('\t\t\t ( Number of Filters, Channels, Rows, Columns )')
      print('\t Padding = ',  self.zero_padding )
      print('\t Stride = ' , self.stride )

      sys.exit('Undefined Values at Boundary of Activation Map: '\
               'Combination of stride, zero padding, last two axis (axis=-1,
-2) of both filters and activation maps is not correct.'\
               'Properties at this layer are printed above. For more, see th
e documentation of "Conv" class')


    #array of zeros for output of convolution operation
    output=np.zeros((activations.shape[0], self.weights.shape[0]) + tuple(ou
tput_row_col.astype(np.int)))

    if train:
      self.output_shape=output.shape

    for filter in range(self.number_of_filters):

      for rows in range(output.shape[-2]):

        for cols in range(output.shape[-1]):

          #adusting values with stride
          r=rows*self.stride
          c=cols*self.stride

          #extract part of image, perform convolution and assign it to new m
ap
          output[:,filter, rows, cols]=np.sum(activations[:,:, r:r + self.we
ights.shape[-2] , c:c + self.weights.shape[-1]] * self.weights[filter,:,:,:]
, axis=(1,2,3)) + self.bias[filter]

    return output

  def backward(self, dL):
    '''
      Calculates gradients with respect to inputs, weights and bias of this
layer
      and returns gradient w.r.t input of shape (same as input to this layer
):

      Parameters:

        'dL' : numpy array of shape (same as output of this layer)
          Global gradient flowing from the next layer

    '''

    if dL.shape != self.output_shape:
```

```
      sys.exit("The shape of global gradient must be same as output of the C
onvlutional layer")

    #gradient w.r.t bias
    self.dB = np.sum(dL, axis=(0,2,3)).reshape(-1,1)

    #gradient w.r.t weights

    #apply zero padding to inputs of the layer
    pw=[[0,0]]*(np.size(self.inputs.shape)-2) + [[self.zero_padding, self.ze
ro_padding]]*2
    X = np.pad(self.inputs, pw, 'constant', constant_values=0)

    self.dW = np.zeros(self.weights.shape)

    #Valid Convolution (X,dL)
    for filter in range(self.number_of_filters):

      for rows in range(self.weights.shape[-2]):

        for cols in range(self.weights.shape[-1]):

          #adusting values with stride
          r=rows*self.stride
          c=cols*self.stride

          #concentenate dL to match depth of weights
          temp=np.concatenate( [dL[:,filter, np.newaxis, :,:]] * X.shape[1],
  axis=1)

          #dW
          self.dW[filter, :, rows, cols]= np.sum(temp*X[:,:, r:r + dL.shape[
-2] , c:c + dL.shape[-1]], axis=(0,2,3))

    #gradient w.r.t inputs

    #apply zero padding to weights of the layer
    pw=[[0,0]]*(np.size(self.weights.shape)-2) + [[dL.shape[-1]-1,dL.shape[-
1]-1]]*2
    W = np.pad(self.weights, pw, 'constant', constant_values=0)

    #calculate shape of dX
    output_row_col = ((np.array(W.shape[-2:]) - dL.shape[-2:]) / self.stride
) +1
    dX = np.zeros((dL.shape[0], self.weights.shape[1]) + tuple(output_row_co
l.astype(np.int)))

    #flip the weights
    W=np.flip(W, axis=(-1,-2))

    #Full Convlution (rotated weights, dL)
    for filter in range(self.number_of_filters):

        for rows in range(dX.shape[-2]):

          for cols in range(dX.shape[-1]):
```

```
            #adusting values with stride
            r=rows*self.stride
            c=cols*self.stride

            #concentenate dL to match depth of weights
            temp=np.concatenate([dL[:,filter, np.newaxis,:,:]]*W.shape[1], axis=1)

            #dX
            dX[:, :, rows, cols] += np.sum(temp*W[filter,:, r:r + dL.shape[-2] , c:c + dL.shape[-1]], axis=(2,3))


    #Flip the result
    dX=np.flip(dX, axis=(-1,-2))

    #remove zero padding and return dX
    return dX[:,:, self.zero_padding:dX.shape[-2]-self.zero_padding, self.zero_padding:dX.shape[-1]-self.zero_padding]

class Tanh:
  '''
    Returns an object of class "Tanh" that can be used as activation function in CNNs

  '''

  def forward(self, activations, train=False):
    '''
      Applies Hyperbolic Tangent function to the input and returns the result

      Parameters:

        'activations' : numpy array
          activations on which tanh function will be applied

        'train' : bool. Default=False
          whether training of the layer is being carried out or not
    '''

    #apply tanh funciton
    output = np.tanh(activations)

    # calculate local gradient
    if train:
      self.output_shape = output.shape
      self.dT = 1-np.square(output)

    return output


  def backward (self, dL):
    '''
      Calculates and returns gradient with respect to inputs to this layer

      Parameters:
```

```
        'dL' : numpy array of shape (same as output of this layer)
          global gradient (flowing from the next layer)

    '''
    if dL.shape != self.output_shape:
      sys.exit("The shape of global gradient must be same as output of the t
anh layer")

    #dX
    return dL*self.dT

class ReLU:
  '''
    Returns an object of "ReLU" class that can be used as activation functio
n in CNNs

  '''


  def forward(self, activations, train=False):
    '''
      Applies ReLU function to the input and returns the result

      Parameters:

        'activations' : numpy array
          activations on which ReLU function will be applied

        'train' : bool. Default=False
          whether training of the layer is being carried out or not
    '''

    #apply ReLU
    output = np.maximum(0, activations)

    #calculate local gradient
    if train:
      self.output_shape = output.shape
      self.dR =  1 * (activations > 0)

    return output


  def backward (self, dL):
    '''
      Calculates and returns gradient with respect to inputs to this layer

      Parameters:

        'dL' : numpy array of shape (same as output of this layer)
          global gradient (flowing from the next layer)

    '''
    if dL.shape != self.output_shape:
      sys.exit("The shape of global gradient must be same as output of the R
eLU layer")
```

```
    #dX
    return dL*(self.dR)

class LeakyReLU:
  '''
    Returns an object of "LeakyRelU" class that can be used as activation fu
nction in CNNs

    Parameters:

      'slope' : int or float. Default=0.01 (optional)
        slope of the function for negative values of input i.e it represents
 'a' in the following formula:

            f(x) = max(ax, x)

  '''
  def __init__(self, slope=0.01):

      self.slope = slope


  def forward(self, activations, train=False):
    '''
      Applies LeakyReLU function to the input and returns the result

      Parameters:

        'activations' : numpy array
          activations on which LeakyReLU function will be applied

        'train' : bool. Default=False
          whether training of the layer is being carried out or not
    '''

    #apply LeakyReLU
    output = np.maximum(self.slope*activations, activations)

    #calculate local gradient
    if train:
      self.output_shape = output.shape
      self.dLR =  np.ones(activations.shape)
      self.dLR [activations < 0] = self.slope

    return output


  def backward (self, dL):
    '''
      Calculates and returns gradient with respect to inputs to this layer

      Parameters:

        'dL' : numpy array of shape (same as output of this layer)
          global gradient (flowing from the next layer)
```

```
    '''

    if dL.shape != self.output_shape:
      sys.exit("The shape of global gradient must be same as output of the L
eakyReLU layer")

    #dX
    return dL*(self.dLR)

class Softmax:
  '''
    Returns an object of "Softmax" class that can be used with cross entropy
 loss in CNNs

  '''

  def forward(self, activations, train=False):
    '''
      Applies Softmax function to the input and returns the result

      Parameters:

       'activations' : numpy array of shape (batch, number_of_classes, 1, 1)
 or (Batch, number of classes)
          activations on which Softmax funciton will be applied

        'train' : bool. Default = False
          whether training of the layer is being carried out or not
    '''

    if train:
      self.input_shape = activations.shape


    #check for correct shape of activations
    if len(activations.shape) == 4:

      if activations.shape[-2:] != (1,1):
        sys.exit("When using Global Average Poooling Technique (i.e the len
of shape of activations is 4),"\
         "it can only be of form (batch, number of classes, 1,1)")
      else:
        activations = activations.reshape(activations.shape[0], activations.
shape[1]) #reshape activations

    elif len(activations.shape) == 2:
      pass

    else:
      sys.exit("The number of dimensions of activations are not correct. It
can either be two or four")


    #unnormalized probabilities
    unnorm_prob = np.exp(activations)  #in order to avoid NaN

    #normalized probabilities
```

```
    output = unnorm_prob / (np.sum(unnorm_prob, axis=1).reshape(-1,1))

    self.activations = output

    #calculate local gradient
    if train:
      self.output_shape = output.shape

      # derivative of this layer results in a jacobian of size (nunber of cl
asses, number of classes) for each example.
      # however, since we are dealing with one hot encoded values, the impor
tant values in jacobian are at the diagonals
      # which are calcualted as follows:
      self.dS = np.multiply(output, (1-output))

    return output

  def backward (self, dL):
    '''
      Calculates and returns gradient with respect to inputs to this layer

      Parameters:

        'dL' : numpy array of shape (same as output of this layer)
          global gradient (flowing from the next layer)

    '''
    if dL.shape != self.output_shape:
      sys.exit("The shape of global gradient must be same as output of the S
oftmax layer")

    #dX
    return (dL*self.dS).reshape(self.input_shape)

class Pool:
  '''
    Returns an object of "Pool" class that can be used as Pooling Layer in C
NNs.

    Paramters:

      'pooling_type' : str = 'max', 'average' or 'global'
        It defines which type of pooling to be applied on the activation map
s. It can take one of the following values:

          'max': outputs maximum value of region of activation map under the
 window
          'average' or 'global': outputs mean value of region of activation
map under the window

      'filter_size' : non-zero, positive, int (optional when using 'pooling_
type' = 'global')
        size of the square window that needs to operate over each activation
 map

      'stride' : non-zero, positive, int. Default=2 (optional)
        size of step to take in horizontal and vertical direction
```

```
      'zero_padding' : positive, int. Default=0 (i.e. no zero padding) (optional)
        number of rows and columns of zeros that needs to be added around each activation map.
          For example, if it is specified to be as 2 and activations has a shape of (batch, channels, rows, cols), then
          after zero padding, the new shape of activations will be (batch, channels, rows + 4, cols + 4) with zeros above and below, right and left of the axis -1 and -2.

  Notes:

    -  Combination of stride, zero padding, last two axis of both filter and activation maps must be
    such that it results in an whole number for the following equation:

              For each axis:
                      O = ( ( R - F + 2P ) / S ) + 1
              where
                      O = size of output axis
                      R = size of activation map axis
                      F = size of filter
                      P = amount of zero padding
                      S = stride

    -  When using 'global' as 'pooling type', following parameters will be set as:

              'filter_size' = size of last two axis of activation map (rows, cols)
              'stride' = 1
              'zero_padding' = 0

       Thus, these parameters are not required. In case, if they are provided then they will be overwritten.

  '''
  def __init__(self, pooling_type, filter_size=None, stride=1, zero_padding=0 ):

    self.pooling_type = pooling_type

    #assign function for corresponding pooling type
    if pooling_type == 'max':
      self.poolFnt=np.max

    elif pooling_type == 'average':
      self.poolFnt=np.mean

    elif pooling_type == 'global':

      self.poolFnt = np.mean
      self.stride = 1
      self.zero_padding = 0

    else:
```

```
      sys.exit("Invalid Value provided for parameter 'pooling_type'.It can o
nly be 'max', 'average' or 'global' (with single quotes).")


    #Check for errors in input values

    if pooling_type != 'global' and filter_size == None:
      sys.exit("When not using 'global' as pooling type, 'filter_size' must
be provided")

    if pooling_type != 'global':

      if filter_size <= 0 or filter_size % 1 != 0:
        sys.exit("Invalid Value provided for parameter 'filter_size'. It mus
t be non-zero, positive integer.")
      else:
        self.filter_size=filter_size

      if stride <= 0 or stride % 1 !=0:
        sys.exit("Invalid Value provided for parameter 'stride'.It must be n
on-zero, positive integer.")
      else:
        self.stride = stride

      if zero_padding < 0 or zero_padding  % 1 !=0:
        sys.exit("Invalid Value provided for parameter 'zero_padding'.It mus
t be positive integer.")
      else:
        self.zero_padding=zero_padding


  def forward(self, activations, train=False):
    '''
      Performs Pooling of the activation maps and returns the result (shape
= (b, d, r, c)):

          b = batch (same as 'activations')
          d = channels (same as 'activations')
          r, c = Rows and Columns (calculated using the formula described in
 the constructor of the class)

      Parameters:

      'activations' : numpy array of shape (batch, channels, rows, columns)
        Activation map upon which pooling will be performed

      'train' : bool. Default = False (optional)
        whether training of the layer is being carried out or not

    '''
    #check whether valid value for activations is provided

    if len(activations.shape) != 4:
      sys.exit("The shape of the activations is incorrect. It must be (batch
, channels, rows, cols). ")

    if activations.shape[-1] != activations.shape[-2]:
```

```
        sys.exit("The rows and columns (i.e axis =-1 and -2) of Activations 
must be same for pooling. ")

    #Adjust filter size for global average pooling
    if self.pooling_type == 'global':
      self.filter_size = activations.shape[-1]

    #Apply Zero padding
    pw=[[0,0]]*(np.size(activations.shape)-2) + [[self.zero_padding, self.ze
ro_padding]]*2 #list of pad widths for each axis
    activations = np.pad(activations, pw, 'constant', constant_values=0)

    # Calculate shape of output
    output_row_col = ( ( np.array(activations.shape[-2:] ) - self.filter_siz
e ) / self.stride) +1

    #check whether filter and activations convolve properly
    if all(output_row_col%1 !=0) :
      print('Properties at this layer:')
      print('\t Layer = Pooling with ', self.pooling_type )
      print('\t Size of Activations (with zero padding) = ', activations.sha
pe )
      print('\t\t\t ( batch, channels, rows, columns )')
      print('\t Size of window = ', (self.filter_size, self.filter_size) )
      print('\t Padding = ',  self.zero_padding )
      print('\t Stride = ' , self.stride )

      sys.exit('Undefined Values at Boundary of Activation Map: '\
               'Combination of stride, zero padding, last two axis (axis=-1,
-2) of both window and activation maps is not correct.'\
               'Properties at this layer are printed above. For more, see th
e documentation of "Pool" class')


    #array of zeros for output of pooling operation
    output=np.zeros((activations.shape[0:2] + tuple(output_row_col.astype(np
.int))))

    if train:
      self.inputs_shape = activations.shape
      self.output_shape = output.shape

      #for storing indices for local gradient
      self.indices=np.empty((output.shape[-2:]), object)


    for rows in range(output.shape[-2]):

      for cols in range(output.shape[-1]):

        #adusting values with stride
        r=rows*self.stride
        c=cols*self.stride

        #pooling
        result=self.poolFnt(activations[:,:, r:r + self.filter_size , c:c + 
self.filter_size], axis=(-2,-1))
```

```
        if train:

          # find indices for local gradient when 'pooling_type' is 'max'
          if self.poolFnt.__name__ == 'amax':

            #indices where highest value occurs
            value_indices = np.where(np.equal(result[:,:,np.newaxis, np.newa
xis], activations[:,:, r:r + self.filter_size, c:c + self.filter_size] ))

            #remove extra indices if multiple highest values exist
            temp = np.array([value_indices[0], value_indices[1], value_indic
es[2], value_indices[3]]).T
            _, uniq_indices = np.unique(np.array([value_indices[0],value_ind
ices[1]]).T, return_index=True, axis=0)

            #store the indices
            self.indices[rows,cols]= tuple([np.array(i) for i in temp[uniq_i
ndices].T ])


        output[:,:, rows, cols] = result


    return output

  def backward(self, dL):
    '''
      Calculates and returns gradients with respect to input of this layer

      Parameters:

      'dL' : numpy array of shape (same as output of this layer)
        Global gradient flowing from the next layer

    '''

    if dL.shape != self.output_shape:
      sys.exit("The shape of global gradient must be same as output of the P
ooling layer")

    dX=np.zeros(self.inputs_shape)

    #calculate Gradient
    for rows in range(dL.shape[-2]):

      for cols in range(dL.shape[-1]):

        #adusting values with stride
        r=rows*self.stride
        c=cols*self.stride

        #dX
        if self.poolFnt.__name__ == 'amax':
          dX[:,:, r:r + self.filter_size , c:c + self.filter_size][self.indi
ces[rows,cols]] += dL[:,:,rows, cols].flatten()
```

```
        else:
          dX[:,:, r:r + self.filter_size , c:c + self.filter_size] += (dL[:,
:,rows,np.newaxis, cols, np.newaxis]/(self.filter_size*self.filter_size))

    #remove zero padding
    return dX[:,:, self.zero_padding:dX.shape[-2]-self.zero_padding, self.ze
ro_padding:dX.shape[-1]-self.zero_padding]

class FC:
  '''
    Returns an object of "FC" class that can be used as fully connected laye
r in CNNs

    Parameters:

      'neurons' : non-zero, positive, int
        Number of Neurons in the Fully Connected Layer
  '''
  def __init__(self, neurons):

    #check whether valid value is provided for 'neurons'
    if neurons <= 0 or neurons % 1 != 0:
        sys.exit("Invalid Value provided for parameter 'neurons'. It must be
 non-zero, positive integer.")
    else:
        self.neurons = neurons

    #variables asscoiated with this layer

    self.weights=np.array([])
    self.dW=np.array([])

    self.bias=np.array([])
    self.dB=np.array([])

  def forward(self, activations, train=False):
    '''
      Performs the following operation and returns the result of shape = (Ba
tch, neurons in this layer)

          result = activations*weight + bias

      Parameters:

        'activations' : numpy array of shape (batch, channels, rows, columns
) or (Batch, neurons in previous layer)
          activations which will be connected to fully connected layer

        'train' : bool. Default = False (optional)
          whether training of the layer is being carried out or not

      Notes:

        -  If 'activations' is of shape (batch, channels, rows columns), the
n it will be reshaped into (Batch, Channels*Rows*Cols)

     '''
```

```
    if train:
      self.inputs_shape = activations.shape

    #Check whether valid values are provided for parameters

    if len(activations.shape) == 4:
      activations = activations.reshape(activations.shape[0], np.prod(activa
tions.shape[1:]))

    elif len(activations.shape) == 2:
      pass

    else:
      sys.exit("The number of dimensions of activations are not correct. It
can either be two or four")


    if self.weights.shape[1] != self.neurons or self.bias.shape[0] != self.n
eurons:
      sys.exit("The number of neurons in weights or bias do not match with n
umber of neurons specified.")

    if activations.shape[1] != self.weights.shape[0]:
      sys.exit("There is a mismatch in number of neurons in previous layer b
etween activations and weights. The second axis of activations do not match
with the first axis of weights.")

    if self.bias.shape[1] != 1:
        sys.exit("Invalid Shape of parameter 'bias'. It must be of shape (nu
mber of neurons,1)")

    self.bias = self.bias

    #Apply the Linear function
    output = np.matmul(activations, self.weights) + self.bias.reshape(1,-1)

    #For gradients
    if train:
      self.inputs = activations
      self.output_shape = output.shape

    return output



  def backward(self, dL):
    '''
      Calculates gradients with respect to weights and bias of this layer.
      It also calculates and returns gradeints w.r.t inputs to this layer.

      Parameters:

      'dL' : numpy array of shape (same as output of this layer)
        Global gradient flowing from the next layer

    '''
    if dL.shape != self.output_shape:
```

```
      sys.exit("The shape of global gradient must be same as output of the F
ully Connected layer")

    #dW
    self.dW = np.dot(self.inputs.T, dL)

    #dB
    self.dB = np.sum(dL, axis=0).reshape(-1,1)

    #dX
    return np.dot(dL, self.weights.T).reshape(self.inputs_shape)

class CELoss:
  '''
    Returns an object of "CELoss" class that can be used as cross entropy lo
ss for Multiclass Classification in CNNs

    Parameters:

      'number_of_classes' : non-zero, positive, int
        Number of classes present in the dataset

      Notes:

        - 'actual_labels' even though not one hot encoded, are used in calcu
lations in such a way that they work like one hot encoded values.

  '''
  def __init__(self, number_of_classes):

    #check whther valid value is provided for 'number_of_classes'
    if number_of_classes <= 0 or number_of_classes % 1 != 0:
      sys.exit("Invalid Value provided for parameter 'number_of_classes'. It
 must be non-zero, positive integer.")
    else:
      self.number_of_classes = number_of_classes


  def forward (self, activations, labels, train=False):
    '''
    Calculates and returns total Cross Entropy loss (not divided by total nu
mber of training examples).

    Parameters:

      'activations' : numpy array of shape (batch, number of classes)
        activations which will used for calculating cross entropy loss

      'labels' : numpy array of shape (batch, 1)
        label of each training example. They must be positive integers and m
ust range between 0 and number_of_classes - 1.

       'train' : bool. Default = False (optional)
          whether training of the layer is being carried out or not

    Notes:
```

```
    - Natural Log is used for the calculation of loss function

  '''

  #Check whether inputs' shape and values are correct

  if activations.shape[1] != self.number_of_classes:
    sys.exit("The number of classes specified do not match with the number
 of neurons in the last layer. These two must be same")

  if activations.shape[0] != labels.shape[0]:
    sys.exit("There is a mismatch in number of examples in activations and
 in labels provided.")

  if labels.shape[1] != 1 or len(labels.shape) != 2:
    sys.exit("The shape of 'labels' is not correct. It can only be (batch,
1)")

  unique_labels = np.unique(labels)

  if any(unique_labels < 0) or any(unique_labels % 1 != 0):
    sys.exit("Invalid Value provided for parameter 'labels'. It can only b
e positive integer.")

  if len(unique_labels) > self.number_of_classes:
    sys.exit("There are more classes in 'labels' than specified.")

  if not set(unique_labels).issubset( range(0, self.number_of_classes) ):
    sys.exit("The integers in 'labels' do no fall in range between 0 and n
umber of classes - 1.")

  #Annotating labels with number of training example
  label_with_img_no = tuple( [range(activations.shape[0]), labels.reshape(
-1)] )

  #calculate local gradient
  if train:
    self.dC = np.zeros(activations.shape, dtype=np.float)
    self.dC [label_with_img_no] = -1/(activations[label_with_img_no])

  #calculate loss
  loss = - np.log( activations[label_with_img_no])

  return np.sum( loss )


 def backward(self, dL):
  '''
    Calculates and returns gradients with respect to inputs of this layer.


    Parameters:

    'dL' : int/float
      Global gradient flowing from the next layer

  '''
```

```
    #dX
    return dL*self.dC

def ClassAccu(activations, actual_labels):
  '''
     Returns number of correctly classified examples in the batch

     Parameters:

       'activations' : numpy array of shape (batch, number of classes)
         activations of output layer (layer before loss function).

       'actual_labels' : numpy array of shape (batch,1)
         actual labels of each example

      Notes:

        - 'actual_labels', even though not one hot encoded, are used in calc
ulations in such a way that they work like one hot encoded values.

  '''

  #indexes of highest values
  pred_labels=np.where(np.max(activations, axis=1, keepdims=True) == activat
ions )

  #remove those rows in case when more than one class have equal highest sco
re
  temp=np.array([pred_labels[0],pred_labels[1]]).T
  _,indices=np.unique(pred_labels[0], return_index=True)

  #calculate and return percentage of correctly classified examples
  return np.sum(temp[indices][:,1] == actual_labels.reshape(-1))

def ConfMatrix(activations, actual_labels):
  '''
     Returns Confusion Matrix (numpy array) of shape (number of classes, num
ber of classes)
         Rows represent predicted labels and Columns represent actual labels
.

     Parameters:

       'activations' : numpy array of shape (batch, number of classes)
         activations of output layer (layer before loss function).

       'actual_labels' : numpy array of shape (batch,1)
         actual labels of each example

    Notes:

    - 'actual_labels', even though not one hot encoded, are used in calculat
ions in such a way that they work like one hot encoded values.
  '''

  #indexes of highest values
```

```
  pred_labels = np.where(np.max(activations, axis=1, keepdims=True) == activ
ations )

  #remove those rows in case when more than one label have equal highest sco
re
  temp = np.array([pred_labels[0],pred_labels[1]]).T
  _,indices = np.unique(pred_labels[0], return_index=True)

  #concentate indices of predicted and actual labels
  temp = np.concatenate((temp[indices][:,1].reshape(-1,1), actual_labels), a
xis=1)

  #confusion matrix
  cm = np.zeros((activations.shape[1], activations.shape[1]))
  for x,y in temp:
    cm[x, y] = cm[x, y] +1

  return cm

class GD:
  '''
    Returns an object of "GD" class that can be used as optimizer in CNNs.
    It uses Vanilla Gradient Descent algorithm to update the parameters.
    Further, it may be noted that it uses L2 regularization

  '''
  def update(self, layer, batch_size, lmbda, lr):
    '''
      Updates parameters of the layer

      Parameters:

        'layer' : object of class 'Conv' or 'FC'
          layer whose weights will be updated

        'batch_size' : non-zero positive int
          size of batch.

        'lmbda' : int or float
          value of regulariztion parameter

        'lr' : int or float
          value of learning rate

    '''
    if type(layer).__name__ == 'Conv' or type(layer).__name__ == 'FC':

      #adjust for regularization and update paramters
      layer.weights += - lr * ((layer.dW + (lmbda*layer.weights))/batch_size
)
      layer.bias += -lr *(layer.dB/batch_size)

    else:
      sys.exit("Invalid Layer for parameters updation")

class GDM:
  '''
```

```
    Returns an object of "GDM" class that can be used as optimizer in CNNs.
    It uses Gradient Descent with Momentum algorithm to update the parameter
s.
    Further, it may be noted that it uses L2 regularization

    Parameters:

      'rho' : int or float
        value of "friction"
  '''
  def __init__(self, rho):
    self.rho = rho


  def update(self, layer, batch_size, lmbda, lr):
    '''
      Updates parameters of the layer

      Parameters:

        'layer' : object of class 'Conv' or 'FC'
          layer whose weights will be updated

        'batch_size' : non-zero postive int
          size of batch.

        'lmbda' : int or float
          value of regulariztion parameter

        'lr' : int or float
          value of learning rate

    '''
    if type(layer).__name__ == 'Conv' or type(layer).__name__ == 'FC':

      #adjust for regularization
      total_dW = (layer.dW + (lmbda*layer.weights))/batch_size
      total_dB = layer.dB/batch_size

      #adjust for first iteration and update weights
      if not hasattr(layer, 'dW_vel'):
        layer.dW_vel = 0

      print('dW_vel inside', dW_vel)
      layer.dW_vel = (self.rho*layer.dW_vel) + total_dW
      layer.weights += - lr * layer.dW_vel

      #adjust for first iteration and update bias
      if not hasattr(layer, 'dB_vel'):
        layer.dB_vel = 0

      layer.dB_vel = (self.rho*layer.dB_vel) + total_dB
      layer.bias += - lr * layer.dB_vel

    else:
      sys.exit("Invalid Layer for parameters updation")
```

```
class NM:
  '''
    Returns an object of "NM" class that can be used as optimizer in CNNs.
    It uses Nestrov Momentum algorithm to update the parameters.
    Further, it may be noted that it uses L2 regularization

    Parameters:

      'rho' : int or float
        value of "friction"
  '''
  def __init__(self, rho):
    self.rho = rho


  def update(self, layer, batch_size, lmbda, lr):
    '''
      Updates parameters of the layer

      Parameters:

        'layer' : object of class 'Conv' or 'FC'
          layer whose weights will be updated

        'batch_size' : non zero positive int
          size of batch.

        'lmbda' : int or float
          value of regulariztion parameter

        'lr' : int or float
          value of learning rate

    '''
    if type(layer).__name__ == 'Conv' or type(layer).__name__ == 'FC':

      #adjust for regularization
      total_dW = (layer.dW + (lmbda*layer.weights))/batch_size
      total_dB = layer.dB/batch_size

      #adjust for first iteration and update weights
      if not hasattr(layer, 'dW_vel'):
        layer.dW_vel = 0

      old_dW_vel = layer.dW_vel
      layer.dW_vel = (self.rho*layer.dW_vel) - (lr * total_dW)
      layer.weights += - (self.rho*old_dW_vel) + ((1+self.rho) * layer.dW_ve
l)

      #adjust for first iteration and update bias
      if not hasattr(layer, 'dW_vel'):
        layer.dB_vel = 0

      old_dB_vel = layer.dB_vel
      layer.dB_vel = (self.rho*layer.dB_vel) - (lr * total_dB)
      layer.bias += - (self.rho*old_dB_vel) + ((1+self.rho) * layer.dB_vel)
```

```
    else:
      sys.exit("Invalid Layer for parameters updation")

class AG:
  '''
    Returns an object of "AG" class that can be used as optimizer in CNNs.
    It uses AdaGrad algorithm to update the parameters.
    Further, it may be noted that it uses L2 regularization

  '''

  def update(self, layer, batch_size, lmbda, lr):
    '''
      Updates parameters of the layer

      Parameters:

        'layer' : object of class 'Conv' or 'FC'
          layer whose weights will be updated

        'batch_size' : non zero positive int
          size of batch.

        'lmbda' : int or float
          value of regulariztion parameter

        'lr' : int or float
          value of learning rate

    '''
    if type(layer).__name__ == 'Conv' or type(layer).__name__ == 'FC':

      #adjust for regularization
      total_dW = (layer.dW + (lmbda*layer.weights))/batch_size
      total_dB = layer.dB/batch_size

      #adjust for first iteration and update weights
      if not hasattr(layer, 'dW_squared'):
        layer.dW_squared = 0

      layer.dW_squared += total_dW * total_dW
      layer.weights += - (lr*total_dW)/(np.sqrt(layer.dW_squared) + 0.000000
01 )

      #adjust for first iteration and update weights
      if not hasattr(layer, 'dB_squared'):
        layer.dB_squared = 0

      layer.dB_squared += total_dB * total_dB
      layer.bias += - (lr*total_dB)/(np.sqrt(layer.dB_squared) + 0.00000001
)

    else:
      sys.exit("Invalid Layer for parameters updation")

class RP:
  '''
```

```
    Returns an object of "RP" class that can be used as optimizer in CNNs.
    It uses RMSProp algorithm to update the parameters.
    Further, it may be noted that it uses L2 regularization

    Parameters:

      'decay_rate' : int or float
        value of rate of decay of learning rate
  '''
  def __init__(self, decay_rate):
    self.decay_rate = decay_rate


  def update(self, layer, batch_size, lmbda, lr):
    '''
      Updates parameters of the layer

      Parameters:

        'layer' : object of class 'Conv' or 'FC'
          layer whose weights will be updated

        'batch_size' : non-zero positive int
          size of batch.

        'lmbda' : int or float
          value of regulariztion parameter

        'lr' : int or float
          value of learning rate

    '''
    if type(layer).__name__ == 'Conv' or type(layer).__name__ == 'FC':

      #adjust for regularization
      total_dW = (layer.dW + (lmbda*layer.weights))/batch_size
      total_dB = layer.dB/batch_size

      #adjust for first iteration and update weights
      if not hasattr(layer, 'dW_squared'):
        layer.dW_squared = 0

      layer.dW_squared = (self.decay_rate * layer.dW_squared) + (( 1 - self.
decay_rate ) * (total_dW * total_dW))
      layer.weights += - ( lr*total_dW )/( np.sqrt(layer.dW_squared) + 0.000
00001 )

      #adjust for first iteration and update weights
      if not hasattr(layer, 'dB_squared'):
        layer.dB_squared = 0

      layer.dB_squared = (self.decay_rate * layer.dB_squared) + (( 1 - self.
decay_rate ) * (total_dB * total_dB))
      layer.bias += - (lr*total_dB)/(np.sqrt(layer.dB_squared) + 0.00000001
)

    else:
```

```
      sys.exit("Invalid Layer for parameters updation")

class AD:
  '''
    Returns an object of "AD" class that can be used as optimizer in CNNs.
    It uses Adam algorithm to update the parameters.
    Further, it may be noted that it uses L2 regularization

    Parameters:

      'beta1' : int or float

      'beta2' : int or float

  '''
  def __init__(self, beta1, beta2):
    self.beta1 = beta1
    self.beta2 = beta2


  def update(self, layer, batch_size, lmbda, lr, iter):
    '''
      Updates parameters of the layer

      Parameters:

        'layer' : object of class 'Conv' or 'FC'
          layer whose weights will be updated

        'batch_size' : non zero postive int
          size of batch.

        'lmbda' : int or float
          value of regulariztion parameter

        'lr' : int or float
          value of learning rate

        'iter' : non zero positive int
          number of iteration

    '''
    if type(layer).__name__ == 'Conv' or type(layer).__name__ == 'FC':

      #adjust for regularization
      total_dW = (layer.dW + (lmbda*layer.weights))/batch_size
      total_dB = layer.dB/batch_size

      #adjust for first iteration and update weights
      if not hasattr(layer, 'dW_first_moment'):
        layer.dW_first_moment = 0
      if not hasattr(layer, 'dW_second_moment'):
        layer.dW_second_moment = 0

      layer.dW_first_moment = (self.beta1 * layer.dW_first_moment) + ( (1-se
lf.beta1) *total_dW)
```

```
      layer.dW_second_moment = (self.beta2 * layer.dW_second_moment) + (( 1 - self.beta2 ) * (total_dW * total_dW))

      first_unbias = layer.dW_first_moment / (1 - self.beta1 ** iter)
      second_unbias = layer.dW_second_moment / (1 - self.beta2 ** iter)

      layer.weights += - ( lr*first_unbias )/( np.sqrt(second_unbias) + 0.00000001 )

      #adjust for first iteration and update bias
      if not hasattr(layer, 'dB_first_moment'):
        layer.dB_first_moment = 0
      if not hasattr(layer, 'dB_second_moment'):
        layer.dB_second_moment = 0

      layer.dB_first_moment = (self.beta1 * layer.dB_first_moment) + ( (1-self.beta1) * total_dB)
      layer.dB_second_moment = (self.beta2 * layer.dB_second_moment) + (( 1 - self.beta2 ) * (total_dB * total_dB))

      first_unbias = layer.dB_first_moment / (1 - self.beta1 ** iter)
      second_unbias = layer.dB_second_moment / (1 - self.beta2 ** iter)

      layer.bias += - ( lr*first_unbias )/( np.sqrt(second_unbias) + 0.00000001 )


    else:
      sys.exit("Invalid Layer for parameters updation")

class Network:

  '''
    Returns an object of 'Network' class that is used for building and training the CNN model.

    Parameters:

      'layers' : list of class objects.
        This list defines the architecture of the network.
        It can be have objects of classes:
          'Conv', 'ReLU', 'Tanh', 'LeakyReLU', 'Pool', 'FC', 'Softmax' or 'CELoss'.


      'weights_init' : int, float, 'Gauss', 'Xavier' or 'He'
        This paramter determines how to initialize the weights in the network.
        It can take one of the following values:

            int or float: all weights will be initialized with this value
            'Gauss' : pick random numbers from simple Gaussian Distribution with specified mean and standard deviation
            'Xavier' : same as 'Gauss' except mean = 0 and standard deviation = 1/sqrt(number of input neurons)
            'He' : same as 'Gauss' except mean = 0 and standard deviation = 1/sqrt(number of input nerons/2)
```

```
      'bias_init' : int, float or 'Gauss'
        This parameter determines how to initialize the biases in the networ
k.

      'mean' : int / float (not optional when using 'Gauss')
        Mean of the Gaussian distribution

      'std' : non negative float (not optional when using 'Gauss')
        Standard Deviation of the Gaussian distribution

      'optimizer' : object of a class
        The methodology to use for updating weights. It can be an object of
one of the following classes:
          'GD', 'GDM', 'NM', 'AG', 'RP', or 'AD'

      'eval_metric' : list of functions: ClassAccu or ConfMatrix (optional).

        metrics on which the model will be evaluated. The list can contain u
pto two values. For more info, see notes.

    Notes:

      - For a CNN with two convolution layers, two pooling layers and two fu
lly connected layer with ReLU as activation function
        and Cross entropy as Loss function, the parameter 'layers' with thes
e classes' objects would look like as follows:

          [Conv, ReLU, Pool, Conv, ReLU, Pool, FC, ReLU, FC, Softmax, CELoss
]

        The layer before loss function is output layer and it must have neur
ons equal to number of classes.

      - When using 'Gauss', weights and biases will use same mean and same s
tandard deviation for initialization.
        When using only for weights (or biases), they must be provided.

      - 'Xavier' performs Xavier initialization and 'He' performs He initial
ization of weights. In either case, parameter 'mean'
        and 'std' are not required. If provided, they will be overwritten.

      - When using 'Xavier' or 'He', the number of input neurons for Convolu
tion layer will be equal to filter_size*filter_size*channels
        and for Fully Connected layer, it will be equal to number of neurons
 in the previous layer.

      - If no value is passed to 'eval_metric', no evaluation method will be
 used. This parameter must be a list.
        It can take any one of the forms: [ClassAccu],[ConfMatrix],[ClassAcc
u, ConfMatrix] or [ConfMatrix,ClassAccu]

  '''
  def __init__(self, layers, weights_init, bias_init,  optimizer, mean=None,
 std=None, eval_metric=None):

    #Check whether valid values are provided for parameter 'layers'
```

```
    possible_layers = ['Conv', 'ReLU',  'Tanh', 'LeakyReLU', 'Pool', 'FC', '
Softmax', 'CELoss']

    if type(layers) != list:
      sys.exit("Invalid Value provided for parameter 'layers'. It must be a
list")
    else:
      uni_layers = np.unique([type(layer).__name__ for layer in layers])

    if len(layers) == 0:
      sys.exit("Invalid Value provided for parameter 'layers'. It cannot be
empty")
    elif not set(uni_layers).issubset(possible_layers):
      sys.exit("Invalid Layer provided.")
    else:
      self.layers = layers


    #Check whether weights/bias' initialization parameters are provided with
 valid values
    if weights_init == 'Gauss' or bias_init == 'Gauss':

      if mean == None:
        sys.exit("Mean must be given when using 'Gauss' for initialization o
f weights/bias")
      else:
        self.mean = mean

      if std == None:
        sys.exit("Standard Deviation must be given when using 'Gauss' for in
itialization of weights/bias")
      elif std < 0:
          sys.exit("Standard Deviation can not be negative")
      else:
          self.std = std


    #Assign corresponding funcitons for weight/bias initialization

    #Flags for constant value parameter initialization
    self.WeightFlag =False
    self.BiasFlag = False

    if (type(weights_init) == int) or (type(weights_init) == float):
      self.WeightInitFnt = self.FillConstValue
      self.WeightFlag =True
      self.WeightValue = weights_init

    elif (weights_init == 'Gauss') or (weights_init == 'Xavier') or (weights
_init == 'He'):
      self.WeightInitFnt = self.GaussDist
      self.WeightValue = weights_init

    else:
      sys.exit("Invalid Value provided for parameter 'weights_init'. It can
either be int, float, 'Gauss', 'Xavier', or 'He'.")
```

```
    if (type(bias_init) ==  int) or (type(bias_init) == float):
      self.BiasInitFnt = self.FillConstValue
      self.BiasFlag =True
      self.BiasValue = bias_init

    elif bias_init == 'Gauss':
      self.BiasInitFnt = self.GaussDist
      self.BiasValue =bias_init

    else:
      sys.exit("Invalid Value provided for parameter 'bias_init'.It can either be int, float, or 'Gauss'.")

    #Check whether valid values for optimizer is provided

    possible_optimizers = ['GD', 'GDM', 'NM', 'AG', 'RP', 'AD']

    if type(optimizer).__name__ not in possible_optimizers:
      sys.exit("Invalid value provided for parameter 'optimizer'")
    else:
      self.optimizer = optimizer

    #Check and assign evaluation metrics
    if (eval_metric != None):

        if len(eval_metric) == 0:
            self.eval_metric = None
        elif len(eval_metric) > 2:
            sys.exit("Too many values for 'eval_metric': The length of list cannot exceed 2.")
        else:
            for metric in eval_metric:

                if metric.__name__ != 'ClassAccu' and metric.__name__ != 'ConfMatrix':
                    sys.exit("Invalid Evaluation Accuracy Metric provided: It can take only these functions: 'ClassAccu' and 'ConfMatrix' ")

        self.eval_metric = eval_metric

    #flag for parameter initialization
    self.flag = True


  def FillConstValue(self, shape, fill_value):
    '''
      Returns array of specified shape, filled with specified value

      Parameters:

        'shape' : tuple of ints
          output shape of the array

        'fill_value' : int or float
          value which will be filled in the array
```

```
    '''
    return np.full(shape, fill_value = fill_value)



  def GaussDist(self, shape, type_init):
    '''
      Returns array of specified shape, whose values obtained randomly from
Gaussian Distribution

      Parameters:

        'shape' : tuple of ints as either (number_of_filters, channels, filt
er_size, filter_size) or (neurons in previous layer, neurons in next layer)
          output shape of array.

        'type_init' : 'Gauss', 'Xavier' or 'He'
          This determines which method to use for initialization of paramete
rs

    '''
    #determine input neurons
    if len(shape) == 4:
      neuron_i = shape[-1]*shape[-2]*shape[-3]

    if len(shape) == 2:
      neuron_i = shape[0]

    if type_init == 'Gauss':
      mean = self.mean
      std = self.std

    elif type_init == 'Xavier':
      mean = 0
      std = 1/np.sqrt(neuron_i)

    elif type_init == 'He':
      mean =0
      std = 1/np.sqrt(neuron_i/2)

    else:
      sys.exit("Unkown Type of parameters Initialization")

    return np.random.normal(mean, std, shape)




  def forward_propagate(self, X, Y, train):
    '''
      Performs forward propagation and returns Loss and accuracy

      Parameters:

        'X' : numpy array of shape (batch, channels, rows, cols)
          batch of input images upon which forward propagation will be carri
ed out
```

```
      'Y' : numpy array of shape (batch,1)
        label of each training example

      'train' : bool
        determines whether function is being called for training or not

  '''

  activations = X


  for layer in self.layers:

    if type(layer).__name__ == 'Conv' and self.flag:

      #intialize parameters
      layer.weights = self.WeightInitFnt((layer.number_of_filters, activat
ions.shape[1], layer.filter_size, layer.filter_size ), self.WeightValue)
      layer.bias = self.BiasInitFnt((layer.number_of_filters,1), self.Bias
Value)


    if type(layer).__name__ == 'FC' and self.flag:

      if len(activations.shape) == 4:
        prev_layer_neurons = activations.shape[-1]*activations.shape[-2]*a
ctivations.shape[-3]
      elif len(activations.shape) == 2:
        prev_layer_neurons = activations.shape[1]
      else:
        sys.exit("Unknown activation shape for Fully Connected Layers")

      #initialize parameters
      layer.weights = self.WeightInitFnt((prev_layer_neurons , layer.neuro
ns), self.WeightValue)
      layer.bias = self.BiasInitFnt((layer.neurons,1), self.BiasValue)


    if type(layer).__name__ == 'CELoss':
      loss = layer.forward(activations, Y, train)

      return loss, accuracy

    else:
      activations = layer.forward(activations, train)


    #Evaluate output on evaluation metrics
    accuracy =[]
    if type(layer).__name__ == 'Softmax' and self.eval_metric != None:

      for metric in self.eval_metric:
        accuracy.append(metric(activations, Y))


  #No initialization of parameters on further calls to this function
```

```
    self.flag=False


  def back_propagate(self):
    '''
      Performs back propagation

    '''
    #Gradient of output of last layer with itself
    dL=1

    for layer in reversed(self.layers):
      dL=layer.backward(dL)



  def update_parameters(self, batch_size, lmbda, lr, iter):
    '''
      Updates parameters of the layers

      Parameters:

        batch_size: non zero postive int
          size of batch. This determines the number of examples after which
weights wiil be updated

        lmbda: int or float
          value of regulariztion parameter

        lr: int or float
          value of learning rate

        iter: nonzero positive int
          number of iteration
    '''
    for layer in self.layers:

      if type(layer).__name__ == 'Conv' or type(layer).__name__ == 'FC':

        if type(self.optimizer).__name__ == 'AD':
          self.optimizer.update(layer, batch_size, lmbda, lr, iter)

        else:
          self.optimizer.update(layer, batch_size, lmbda, lr)





  def gradient_check(self, X, Y):
    '''
      Performs checking of the analytically calculated gradients using numer
ical approach.
      Also prints the dictionary which shows original parameters, original d
erivatives, calculated derivatives and percentage difference.
```

```
      Parameters:

        X: numpy array of shape (batch, channels, rows, cols)
          batch of input images.

        Y: numpy array of shape (batch,1)
          labels of each training example

    '''
    #dictionary for storing parameters and derivatives (original, calculated
, difference percentage) of layers
    grad_network={}

    for layer in self.layers:

      layer_name = type(layer).__name__

      if layer_name == 'Conv' or layer_name == 'FC':

        grad_network[layer_name] = {}

        #store original parameters and derivatives
        grad_network[layer_name]['weights_ori'] = layer.weights
        grad_network[layer_name]['bias_ori'] = layer.bias
        grad_network[layer_name]['deriv_weights_ori'] = layer.dW
        grad_network[layer_name]['deriv_bias_ori'] = layer.dB

        #for storing deivative calculated numerically
        deriv_weights_num = np.zeros(layer.weights.shape)
        deriv_bias_num = np.zeros(layer.bias.shape)

        #small value to be added to each parameter
        e = 0.00001

        if layer_name == 'Conv':

          #For weights
          for filter in range(layer.weights.shape[0]):
            for channels in range(layer.weights.shape[1]):
              for rows in range(layer.weights.shape[2]):
                for cols in range(layer.weights.shape[3]):

                  epsilon = np.zeros(layer.weights.shape)
                  epsilon[filter, channels, rows, cols] = e
                  cost = []

                  #in first iteration add the epsilon value and calculate co
st
                  #in second iteartion subtract the epsilon value and calcul
ate cost
                  for k in range (0, 2, 1):


                    if k==0:
                      layer.weights = grad_network[layer_name]['weights_ori'
] + epsilon
```

```
                    else:
                      layer.weights = grad_network[layer_name]['weights_ori'
] - epsilon

                    #forward propagation
                    c, _ = self.forward_propagate(X, Y, train=False)

                    #store cost
                    cost.append(c/X.shape[0])

                  #calculate and store numerically calculated derivative
                  deriv_weights_num[filter, channels, rows, cols] = (cost[0]
-cost[1])/(2*e)

        if layer_name == 'FC':

          #For Weights
          for neurons_prev in range(layer.weights.shape[0]):
            for neurons_next in range(layer.weights.shape[1]):

              epsilon = np.zeros(layer.weights.shape)
              epsilon[neurons_prev, neurons_next] = e

              cost = []

              #in first iteration add the epsilon value and calculate cost
              #in second iteartion subtract the epsilon value and calculate
cost
              for k in range (0, 2, 1):

                if k==0:
                  layer.weights = grad_network[layer_name]['weights_ori'] +
epsilon

                #forward propagation
                c, _ = self.forward_propagate(X, Y, train=False)

                #store cost
                cost.append(c/X.shape[0])

              #calculate and store numerically calculated derivative
              deriv_weights_num[neurons_prev, neurons_next] = (cost[0]-cost[
1])/(2*e)

        #Calculate percentage difference
        grad_network[layer_name]['deriv_weights_num'] = deriv_weights_num
        grad_network[layer_name]['deriv_weights_diff_percentage'] =  np.abs(
grad_network[layer_name]['deriv_weights_num'] - grad_network[layer_name]['de
riv_weights_ori'])*100

        #For Bias

        layer.weights = grad_network[layer_name]['weights_ori']

        for filter in range(layer.bias.shape[0]):

          epsilon = np.zeros(layer.bias.shape)
```

```
          epsilon[filter] = e

          cost = []

          #in first iteration add the epsilon value and calculate cost
          #in second ieartion subtract the epsilon value and calculate cost
          for k in range (0, 2, 1):

            if k==0:
              layer.bias = grad_network[layer_name]['bias_ori'] + epsilon

            else:
              layer.bias = grad_network[layer_name]['bias_ori'] - epsilon


            #forward propagation
            c, _ = self.forward_propagate(X, Y, train=False)

            #store cost
            cost.append(c/X.shape[0])

          #calculate and store numerically calculated derivative
          deriv_bias_num[filter] = (cost[0]-cost[1])/(2*e)

        #Calculate percentage difference
        grad_network[layer_name]['deriv_bias_num'] = deriv_bias_num
        grad_network[layer_name]['deriv_bias_diff_percentage'] =  np.abs(gra
d_network[layer_name]['deriv_bias_num'] - grad_network[layer_name]['deriv_bi
as_ori'])*100

        layer.bias = grad_network[layer_name]['bias_ori']

    #print the network for verification of derivative calculation
    for p in grad_network:
      print(f'{p}\n')
      for o in grad_network[p]:
        print(f'{o}:\n {grad_network[p][o]}\n')




  def train(self, data, train_batch_size, valid_batch_size, epcohs, lmbda, l
r, grad_check=False):
    '''
      Performs training of the model and returns training and validation cos
t and accuracy for each iteration

      Parameters:

        data: object of class 'Dataset'
          the data which will be used for training and validation

        train_batch_size: int
          size of batch for training data. This determines the number of exa
mples after which weights wiil be updated

        valid_batch_size: int
```

```
          size of batch for validation data.

        epochs: int
          number of times whole dataset needs to be passed through the netwo
rk during training

        lmbda: int or float
          value of regulariztion parameter.

        lr: int or float
          value of learning rate

        grad_check: bool
          whether to calculate and check numerically calculated gradients wi
th analytically calculated gradients

      Notes:

        - The optimizer algorithm uses L2 regularization.

    '''

    #temporary lists for storing the cost and accuracy values in each iterat
ion
    train_cost_iter=[]
    train_accu_iter=[]
    valid_cost_iter=[]
    valid_accu_iter=[]

    for epoch in range(epochs):

      for b in range (0, data.train_data.shape[0], train_batch_size):

        #Training

        #load data
        train_X,train_Y = data.load_data(flag='train', batch = [b, b + train
_batch_size])

        #forward propagation
        train_cost, train_accu = self.forward_propagate(train_X, train_Y, tr
ain=True)

        #store training cost and accuracy
        train_cost_iter.append(train_cost/train_X.shape[0])
        train_accu_iter.append((train_accu[0]/train_X.shape[0])*100) #Store
Classification Accuary percentage

        #back propagation
        self.back_propagate()

        #Estimate Gradient Numerically
        #as this is a slow process, the code will run only for first batch a
nd terminate
        if grad_check:
          self.gradient_check(train_X, train_Y)
          break
```

```
        #Valdiation

        valid_cost=0
        valid_accu=0

        for v in range(0, data.valid_data.shape[0], valid_batch_size):

          valid_X, valid_Y = data.load_data (flag='valid', batch = [v, v + valid_batch_size] )

          cost, accu = self.forward_propagate(valid_X, valid_Y, train=False)

          valid_cost += cost
          valid_accu += accu[0]

        #store validation cost and accuracy
        valid_cost_iter.append(valid_cost/data.valid_data.shape[0])
        valid_accu_iter.append((valid_accu/data.valid_data.shape[0])*100)

        print('Epoch: ', epoch+1, '/', epochs, ' Iteration: ', int((b/train_batch_size)+1), ' Training Loss: ', train_cost/train_X.shape[0], ' Training Accuracy: ',\
               (train_accu[0]/train_X.shape[0])*100,  '%  Validation Loss: ', valid_cost/data.valid_data.shape[0], ' Validation Accuracy: ',\
               (valid_accu/data.valid_data.shape[0])*100, '%')

        #update parameters
        self.update_parameters(train_batch_size, lmbda, lr, iter=(b/train_batch_size)+1)

      if grad_check:
        break


    return train_cost_iter, train_accu_iter, valid_cost_iter, valid_accu_iter

def plot_graph (x1, x2, legends, ylabel, title):
  '''
    Plots graph of 'x1' and 'x2' on same figure

    Parameters:

      'x1': list of float
        values for first graph

      'x2': list of float
        values for second graph

      'legends': list of str
        legend for each graph

      'ylabel': str
        label for y-axis

      'title': str
```

```
        title of the graph

  '''
  plt.plot(x1,  label=legends[0])
  plt.plot(x2, label=legends[1])
  plt.title(title)
  plt.xlabel('Iterations')
  plt.ylabel(ylabel)
  plt.legend()
  plt.axis()
  plt.show()

def disp_F1_score(score, classes):
  '''
    displays Confusion Matrix and F1 table

    Parameters:

      score: list of numpy arrays
        Confusion matrix on first index (shape=(number_of_classes, number_of
_classes))
        and F1 table on second index (shape=(number of classes, 3))

      labels: list
        labels in dataset
  '''
  display(pd.DataFrame(score[0], columns=classes, index=classes))
  display(pd.DataFrame(score[1], columns=['Precision', 'Recall', 'F1 score']
, index=classes))

def plot_weights(filters):
  '''
    Visualize weights in Convolutional Layer

    Parameters:

      'filters' : numpy array of shape (number_of_filters, channels, rows, c
ols)
        weights associated with Convolution layer which need to be plotted
  '''
  count =1
  #for each filter
  for f in range(filters.shape[0]):

    #for each channel
    for d in range(filters.shape[1]):

      plt.subplot(filters.shape[0], filters.shape[1], count)
      plt.imshow(filters[f,d], cmap='gray')

      if not f>0:
        plt.title('Channel ' + str(d+1))

      if not d > 0:
        plt.ylabel('Filter ' + str(f+1))

      count += 1
```

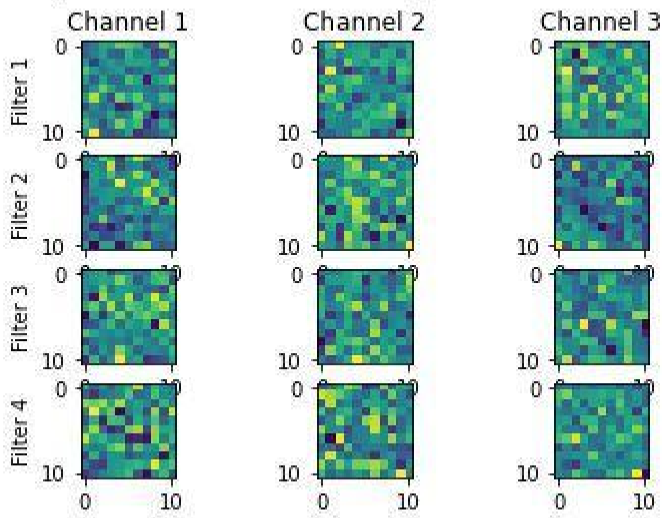
```
def calculate_error(model, data, data_type):

  '''
    Calculates and displays loss, Classification Accuracy, Confusion Matrix
and F1 score on specified dataset

    Parameters:

      'model' : object of class 'Network'
        trained model which will be used for making prediction

      'data' : object of class 'Dataset'
        same object of Dataset which was used for training the model

      'data_type' : str 'train', 'valid' or 'test'
        the data on which prediction needs to be carried out. It can take on
e of the three values.

  '''
  #Determine number of images
  if data_type == 'train':
    noOfimages = data.train_data.shape[0]

  elif data_type == 'valid':
    noOfimages = data.valid_data.shape[0]

  elif data_type == 'test':
    noOfimages = data.test_data.shape[0]

  else:
    sys.exit("Invalid Value for parameter 'data_type'. It can only be 'train
', 'test', or 'valid'")

  batch_size = 512
  total_cost = 0
  total_accu = 0
  confusion_matrix = np.zeros((len(data.labels), len(data.labels)))


  for b in range (0, noOfimages, batch_size):

    #load data
    X, Y = data.load_data(flag='train', batch = [b, b + batch_size])

    #forward propagation
    cost, accu = model.forward_propagate(X, Y, train=True)

    #store cost, classification accuracy and consfusion matrix
    total_cost += cost
    total_accu += accu[0]
    confusion_matrix += accu [1]

  #precision, recall and f1 score table
  tab = np.zeros((len(data.labels), 3))
```

```
  for label in range(len(data.labels)):

    TP = confusion_matrix[label,label] #true positive
    FP = np.sum(confusion_matrix[label,:]) - TP #false positive
    FN = np.sum(confusion_matrix[:,label]) - TP #false negative

    #calculate F1 score
    precision = TP/(TP+FP)
    recall = TP/(TP+FN)
    f1 = 2*precision*recall/(precision+recall)

    tab[label] = np.array([precision, recall, f1])

  #Display results
  print ("The total cost on ", data_type, " data is ", total_cost/noOfimages
)
  print("The Classification Accuracy on ", data_type, " data is ", (total_ac
cu/noOfimages)*100)
  print()
  disp_F1_score([confusion_matrix, tab], data.labels)

path_to_data = '/content/drive/MyDrive/PBC_dataset_normal_DIB'
data = Dataset(path_to_data, resize=(50,50), zero_center='image' )
Conv4 = Conv(number_of_filters=4, filter_size=11, stride=1, zero_padding=1)
LReLU4= LeakyReLU()
Pool4= Pool('max', filter_size=2, stride=2)
Conv8= Conv(number_of_filters=8, filter_size=3, stride=1, zero_padding=1)
LReLU8= LeakyReLU()
Pool8= Pool('max', filter_size=3, stride=2)
FC200 = FC(neurons=200)
LReLU200 = LeakyReLU()
FC8 = FC(neurons=8)
SM = Softmax ( )
CE = CELoss (number_of_classes=8)
layers=[Conv4, LReLU4, Pool4, Conv8, LReLU8, Pool8, FC200,LReLU200, FC8, SM,
 CE]
#setting up hyperparameters
weights_init='He'
bias_init=0.01
eval_metric = [ClassAccu, ConfMatrix]
optimizer = AD( beta1=0.9, beta2=0.999)
train_batch_size = 768
valid_batch_size = 1024
epochs = 2
lmbda = 0.001
lr = 0.0001

#train
model=Network(layers=layers, weights_init=weights_init, bias_init=bias_init,
 optimizer=optimizer, eval_metric=eval_metric  )
train_cost_iter, train_accu_iter, valid_cost_iter, valid_accu_iter = model.t
rain(data, train_batch_size, valid_batch_size, epochs, lmbda, lr)

plot_graph(train_cost_iter, valid_cost_iter, legends= ['Training', 'Validati
on'], ylabel= 'Cost', title = 'Changes in Loss with each Iteration' )
```

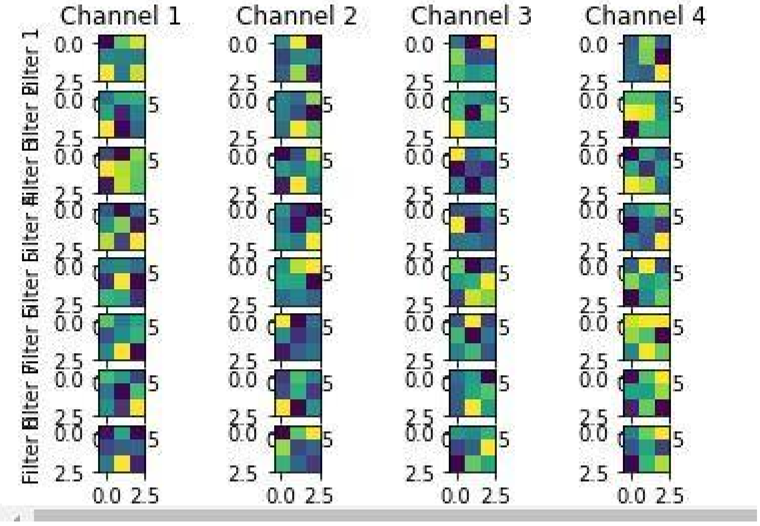
```
plot_graph(train_accu_iter, valid_accu_iter, legends= ['Training', 'Validati
on'], ylabel= 'Classification Accuracy', title = 'Evaluation of Model on Cla
ssification Accuracy (error metric)' )

print("For Convolutional layer, the shape of weights is (number of filters,
channels, rows, columns)")
print("and of bias is (number of filters, 1).")
print()
print("For Fully Connected layer, the shape of weights is (number of neurons
 in previous layer, number of neurons in this layer)")
print(" and of bias is (number of neurons in this layer, 1).")

conv_counter = 1
fc_counter = 1
for layer in model.layers:
    if type(layer).__name__ == 'Conv':
      print("Convolutional Layer ", conv_counter)
      print()
      print("Weights: ")
      print(layer.weights)
      print("Bias ")
      print(layer.bias)
      print()
      conv_counter +=1

    if type(layer).__name__ == 'FC':
      print("Fully Connected Layer ", fc_counter)
      print()
      print("Weights: ")
      print(layer.weights)
      print("Bias ")
      print(layer.bias)
      print()
      fc_counter +=1

conv_counter=1
for layer in model.layers:
  if type(layer).__name__ == 'Conv':
    print("Filters of Convolutional Layer Number: ", conv_counter)

    plot_weights(layer.weights)

    conv_counter += 1

with open('/content/Model.npy', 'wb') as file:

  np.save(file, data.resize) #save resizing of image

  np.save(file, data.mean) #save zero centering info

  np.save(file, data.labels) #save labels

with open('/content/Model.npy', 'ab') as file:

  #save layers except loss function
  layers=[type(layer).__name__ for layer in model.layers[:-1]]
  np.save(file,  layers)
```

```python
  #save parameters and other associated hyperparameters

  for layer in model.layers[:-1]: #except loss function

    if type(layer).__name__ == 'Conv':

      np.save(file, layer.stride)
      np.save(file, layer.zero_padding)
      np.save(file, layer.weights)
      np.save(file, layer.bias)

    if type(layer).__name__ == 'Pool':

      np.save(file, layer.pooling_type)
      np.save(file, layer.filter_size)
      np.save(file, layer.stride)
      np.save(file, layer.zero_padding)

    if type(layer).__name__ == 'FC':

      np.save(file, layer.neurons)
      np.save(file, layer.weights)
      np.save(file, layer.bias)


calculate_error(model, data, 'train')

calculate_error(model, data, 'valid')

calculate_error(model, data, 'test')
```

Convolutional Layer 1 with 4 filters and 3 channels:



Convolutional Layer 2 with 8 filters and 4 channels:



Channel 1
Channel 2
Channel 3
Channel 4

Annex C: Prediction Code

```
import numpy as np
import pandas as pd
import sys
import os
from PIL import Image as pilimg

def prediction(path):
  '''
    Displays a table having image, predicted class and its probability as it
s columns and rows as each image.

    Parameters:

      'path' : str
        path to folder containing the images on which prediction is required


    Notes:

      - The function requires model and some helper functions which are obta
ined from "Model.npy" and "CNN_Training_Code.py" respectively.
        Thus, these two files must be in the same dir as that of this file "
CNN_Prediction_Code.py".
        Furthermore, the names of the files must not be different or the cod
e will break.

      - The function expects images to be of "jpg" format and of type "uint8
"

  '''

  #check whether directory is provided
  if not os.path.isdir(path):
    sys.exit("Invalid Path provided. The path must be to a valid directory")

  #ignore files that do not end with ".jpg"
  path_to_images = [os.path.join(path, image) for image in os.listdir(path)
if image.endswith(".jpg")]
  noOfImages = len(path_to_images)


  #check whether images exists in the directory
  if noOfImages == 0:
    sys.exit("No image found in the directory")
  else:
    print((noOfImages), " Images found")

  #Check whether helper functions file and model exists in the current direc
tory
  helper_functions_file = 'CNN_Training_Code.py'
  model = 'Model.npy'
```

```
  curr_dir = os.getcwd() #current working directory

  if model not in os.listdir(curr_dir):
    sys.exit('"Model Not found: Make sure "Model.npy" is in the same directo
ry of this file and is named properly. ')
  else:
    print("Model found")
    model = os.path.join (curr_dir, model)

  if helper_functions_file not in os.listdir(curr_dir):
    sys.exit('"Helper funcitons file Not found: Make sure "CNN_Training_Code
.py" is in the same directory of this file and is named properly. ')
  else:
    print("Helper functions file found") #remove



  #Import classes from the helper function
  from CNN_Training_Code import Network, Conv, Pool, LeakyReLU, FC, Softmax

  #read data from the file in the same order as it was written to it
  with open(model, 'rb') as file:

    #read size of input to the network
    resize = np.load(file)

    #read zero center related data
    mean = np.load(file)


    #read labels
    labels = np.load(file)

    #read layers
    layers = np.load(file, allow_pickle=True)

    #load parameters and other assiocated data and build each layer
    layer_objs =[]

    for layer in layers:


      #Convolutional Layer
      if layer == 'Conv':

        stride = np.load(file)
        zero_padding = np.load(file)
        weights = np.load(file)
        bias = np.load(file)

        conv = Conv(number_of_filters=weights.shape[0], filter_size=weights.
shape[2], stride=stride, zero_padding=zero_padding)
        conv.weights = weights
        conv.bias = bias

        layer_objs.append(conv)
```

```
        #Pooling Layer
        if layer == 'Pool':

          pooling_type =np.load(file)
          filter_size = np.load(file)
          stride = np.load(file)
          zero_padding = np.load(file)

          layer_objs.append(Pool(pooling_type=pooling_type, filter_size=filter
_size, stride=stride, zero_padding=zero_padding))

        #Fully Connected Layer
        if layer == 'FC':

          neurons = np.load(file)
          fc= FC(neurons)
          fc.weights = np.load(file)
          fc.bias = np.load(file)

          layer_objs.append(fc)

        #LeakyReLU
        if layer == 'LeakyReLU':

          layer_objs.append(LeakyReLU())

        #Softmax
        if layer == 'Softmax':

          layer_objs.append(Softmax())


    class AD:
      pass

    #build network
    net = Network(layer_objs, 0, 0,  AD())
    net.flag=False
    net.eval_metric = None


    #build batch of images
    for image in path_to_images:

      #Read image
      img = pilimg.open(image)

      #Resize image
      img =img.resize(resize)

      img = np.asarray(img)

      #map image between 0 and 1
      img  = img / 255
```

```
    #zero center the data
    img = img - mean

    #reshape image to (depth, width, height)
    img = np.array([img[:,:,0],img[:,:,1],img[:,:,2]])


    net.forward_propagate(img[np.newaxis,...], None, False )

    #indexes of highest values (prediction)
    pred_labels=np.where(np.max(net.layers[-1].activations, axis=1) == net.l
ayers[-1].activations )

    print("the predicted label for image ", image ," is ", labels[pred_label
s[1]], "with ", net.layers[-1].activations[pred_labels]*100, " probability "
)


path_to_images_folder = '/content/drive/MyDrive/Prediction'
prediction(path_to_images_folder)
```