[[1]](#footnote-1)

Image Classification using different datasets on Convolutional Neural Networks

Vaishali Shukla, Thanuja Yarremreddy, Pruthvi Kasani

*Abstract*— In this paper, we examine CNN models employing a variety of datasets, including Cifar 10, Cifar 100, and Fashion MNIST. Finally, we attempt to compare the data and draw a conclusion.

# Introduction

This document explains why we chose this problem description and discusses some potential solutions. So we'll start with the CNN Model before moving on to the problem statement and other topics.

TheAmostAprevalentAneuralAnetworkAmodelAforAimage categorizationAisAconvolutionalAneuralAnetworks(CNNs).

CNNs'AmainApremiseAisAthatAaAlocalAknowledgeAofAan imageAisAsufficient.TheApracticalAbenefitAisAthatAhaving fewerAparametersAspeedsAupAlearningAandAminimizesAtheAamountAofAdataAneededAtoAtrainAtheAmodel.AACNN hasAjustAenoughAweightsAtoAlookAatAaAtinyAportionAof theAimageAinsteadAofAaAfullyAconnectedAnetworkAofA

weightsAfromAeachApixel.It'sAlikeAreadingAaAbookAwith a magnifying glass: youA eventuallyAreadAtheAentireApage, butAyouAonlyAlookAatAaAsmallAportionAofAitAatAaA

time.

# Problem Statement

The Image Classification issue is as follows:given a group of photographs all classified with the same category,weAare askedAtoAforecastAtheseAcategoriesAforAaAnewAsetAof testAimagesAandAquantifyAtheAaccuracyAofAour predictions. ThisAassignmentAhasAaAnumberAofAproblems, which we attempt to address in order to produce a good model with reasonable accuracy.

# Related Work

The CNN model is favoured over the other models, according to this section of the paper. It also depends on a variety of elements such as parameters, network, and so on. The basic principle behind CNN is that the filters work together to scan the entire feature matrix while also reducing the dimensions. One of the main reasons why CNN is a good fit for picture classification and processing is because of this.

Later, we determined that CNNs are effective for image classification since the dimensionality reduction idea is well suited to the large number of parameters in an image.

# Datasets

We employed three different types of datasets in this project: Cifar 10, Cifar 100, and Fashion MNIT databases. We'll go over this in more detail below:

## Cifar 10:

TheACIFAR10AdatasetAcontainsA60000A32x32AcolorA

imagesAdividedAintoAtenAclasses,eachAwithA6000 images.ThereAareA50000AphotosAforAtrainingAand 10,000AimagesAforAtesting.

EachAofAtheA10000AphotosAinAtheAdatasetAis separatedAintoAfiveAtrainingAbatchesAandAoneAtestAbatch. TheAtestAbatchAcontainsAexactlyA1000AphotosAfrom eachAclass,chosenAatArandom. TheAremainingAphotographs areArandomlyAdistributedAamongAtheAtrainingAbatches, howeverAcertainAtrainingAbatchesAmayAcontainAmore imagesAfromAoneAclassAthanAothers.TheAtrainingAbatchesAcontainAexactlyA5000AphotosAfrom each class between them.

The classes are absolutely incompatible. Automobiles and trucks are not interchangeable. Automobiles include sedans, SUVs, and similar vehicles. Only large trucks are classified as "trucks." Both do not include pickup trucks.

## Cifar 100:

The CIFAR-100 dataset contains 60000 32x32 color images divided into 100 classes, each with 600 images. Each class has 500 training photos and 100 assessment images. There are 50000 photos for training and 10,000 images for testing. Twenty super classes are formed from the 100 classes. Each image has two labels: a fine label (real class) and a coarse label (superclass).

## Fashion-MNIST:

Fashion-MNIST is a Zalando article picture dataset that includes a training set of 60,000 samples and a test set of 10,000 examples. Each sample is a 28x28 grayscale image with a label from one of ten categories.

Each image has a height of 28 pixels and a width of 28 pixels, for a total of 784 pixels. Each pixel has a single pixel-value that indicates its lightness or darkness, with larger numbers signifying darker pixels. This pixel value is an integer ranging from 0 to 255. There are 785 columns in the training and test data sets. The firstAcolumnAindicatesAtheAarticleAof clothingAandAcontainsAtheAclassAdesignations (see above). TheApixelAvaluesAofAtheAcorrespondingAimageAareAcontainedAinAtheAremainingAcolumns.

Labels of this dataset include:

* 0 AT-shirt/top
* 1 ATrouser
* 2 APullover
* 3 ADress
* 4 ACoat
* 5 ASandal
* 6 AShirt
* 7 ASneaker
* 8A Bag
* 9 AAnkle boot

# Preprocessing

We'll try to process the data before fitting it into the model in this stage.

* We begin by importing the necessary libraries and dataset from the keras.
* We then separate the data into two categories: testing and training.
* Now we're trying to get the overall number of labels that have been classified as well as the unique label
* The shapes of testing and training data are now printed.
* Next part is to visualize the dataset. So, we print the 15 rows and 15 columns of images in form a matrix.
* We convert the variables y\_train, y\_test from the decimal values into binary i.e., one-hot encoding.
* Now, we reshape the model to have a single channel.
* We print the shape to check if it has the single channel.

# We use the same procedure for all three datasets, with a few exceptions (for example we just reshape and normalize the data from the dataset cifar 100).

# Model

In this step, we will train the model, evaluate it and predict it with the testing data.

* Build the network.
* First created a Con2D to perform convolution process.
* Create 32 filters where each filter consists of 3\*3 matrix with an activation function of RELU.
* Input shape is dimension of image which is 28\*28 needed for Input layer.
* Increase the depth of the network by adding more layers.
* Create a fully connected artificial neural network which uses Dense
* Since we have 10 classes, and dataset has 10 classes, so output must have 10 values.
* Now, we compile model and SGD optimizer.
* Use fit method to train the model using training data.
* Final evaluation of the model using testing data and get the score.
* Feed the x\_data into the model and determining what are the predicted classes going to be.
* Comparing the predicted classes to the true label(y\_test)
* Returning all the binary value to decimal to compare with predicted classes.
* Reshaping x\_test to plot the matrix for prediction
* Confusion Matrix to summarize all the results in one location.
* Later, we can also add more layers and do a dropout to see the prediction results.

A screenshot of a video game

Description automatically generated with medium confidence

A picture containing qr code

Description automatically generated

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