Gender Recognition from Face Images Using Tensor Flow

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Abstract: *Computer vision is the abilityofcomputers to recognizethe objects just like human perception. Genderrecognition fromfaceimages isdonebythe computer afterretrainingthe penultimate layer of the tensorflow architecture.*

Thepresent paperemphasizeson the task of facialgender classification from an image. Ourtrials focuses on usingtensorflowand inception model for this purpose. The classification of gender has significant uses in the arenaof security,marketingand otherfields. Herewedenotethepotential ofthe proposed system on the dataset whereweaccomplished anaccuracyrate of97.5 percent.

Keywords:*Computer Vision, tensorflow architecture.*

I. INTRODUCTION

Since many years the frequency of feeding an image to the web interface has increased in a rapid pace. The new data driven environment has strengthened researchers to solve various problems inthe field of computer vision that was non-existent earlier. Gradually, we saw the raise of effective facial recognition platforms and libraries like OpenCv. The application sof OpenCV encompasses like tagging in instagram to number plate detection. Whereas the consequent work is not about face detection but the features of them. The motto of this project is the samething to classify gender off ace in the image.

The utilizations of the current technology has a wide radar and the prospective to create a legacy. In situations where various languages have variety of vocabulary when identifying man and woman. Henceforth automated identification works and related kind could enhance the reinterpretation. With the thought of the gender of a subject simplifies the recognition process. That would be utilized to help assisted vision systems for those who are blind. Various social networking sites like instagram can utilize the data of the gender of a person to enhance the conditions about an image. Consider a situation where a person is seen playing musical instrument, instagram can label the scenario with music session. But it would be of great impact if it can also predict it as a 'man or woman playing amusical instrument'.

Gender classification is a tough task than many others in computer vision. The main problem for these anomalies is due to the kind of the data which is required to train the system. Whereas the object classification will usually have opportunities to much number of images for training, datasets alongside gender labels are very few in number. A possible cause is that for having labels in such images we should be permitted to use the protected data of subjectsinanimage.Toname it we wouldneedthegender.Henceforth we have to use retraining and tensor flow to neutralize those constraints.

The input data to the code is the face image of a person. The face image is fed to penultimate layer of Inception model. The soft max layer of tensor flow returns the probability of man or woman with an accuracybetween zeroand one.

II. RELATED WORK

The domain of gender classification is being studied since many years; obsolete approaches were used since a long time to solve the problem, with various heights of triumphs. Previous trials emphasized on the recognition of facial characteristics and focused on the variations Among those characteristics and set offeatures.

The characteristicsinthosemethodsencompassed thefeaturesof eyes,nose,andthedifferences betweenthem.Althoughfew ofthe previoustrials were effectiveon inputimages with constraints imposedonthem,thosewere angle visibility, exposureeffects,some[1]did attemptto solvethe constraintswhichdawneddue toconstraintsin images.

A completemethodimplementationtogender classification can befound in[3]. Earlierneural networkswere implemented for the classification ofgender[2].Astimepassed by[4]tooktheaidof supportvectormachines(SVM) anditwasseen thatitattainedadecentaccuracy despitelow resolution.Eventhoughany ofitdidn'tlookto admitthe constraintsof trainingandtestdata that causeddiscrepanciesinthereenvironmentwhere images are subject to various noises and such otherdisturbances.

III. METHODOLOGY

3.1 Networkarchitecture

The network architectureusedinthisprojectis based ontensorflowand inception model. A imageisgiven asinputtothe networkwhere the penultimate layeroutputsthe gender whichis visualized through the ultimatelayer.

Scientistshave achievedrapidgrowthincomputer visionbycomparingwithImageNet.ImageNetis a benchmarkfor computer vision. We have currentlyusedInception-V3 model forthe purpose of genderrecognition.Inception-V3 was trained for theImageNetLargeVisualRecognition Challengeusing thedatafrom2012.Thisisa standardtaskincomputervision,wheremodels try toclassifyentireimagesinto1000classes,like "Leopard","Tiger".Here are theresultsfrom AlexNet classifyingsomeimages:

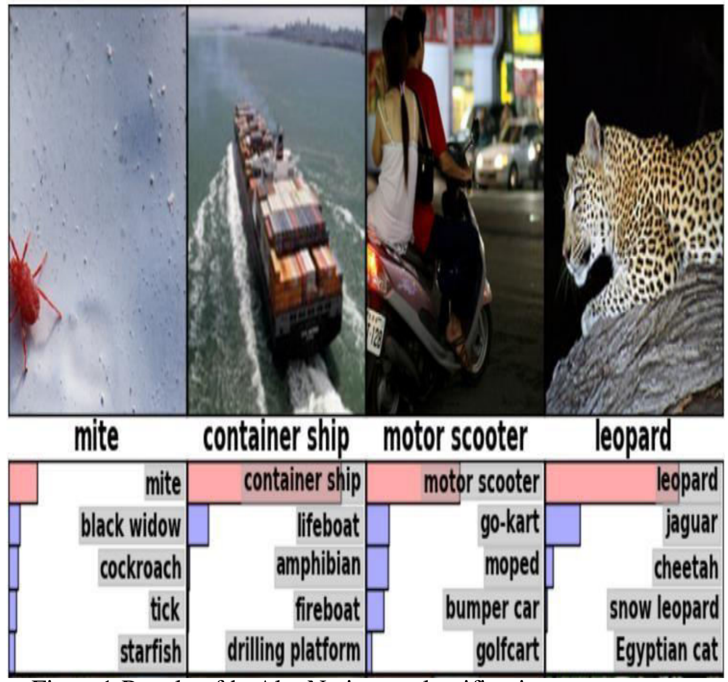

Figure1:ResultsoftheAlexNetimageclassification.

Themodulebasicallyacts as multiple convolution filters, thatare applied to thesame input with some pooling. Theresults arethenconcatenated. This allows themodel to take advantageof multi-level featureextraction.For instance, itextracts general(5*5) and local (1*1)features at thesame time.

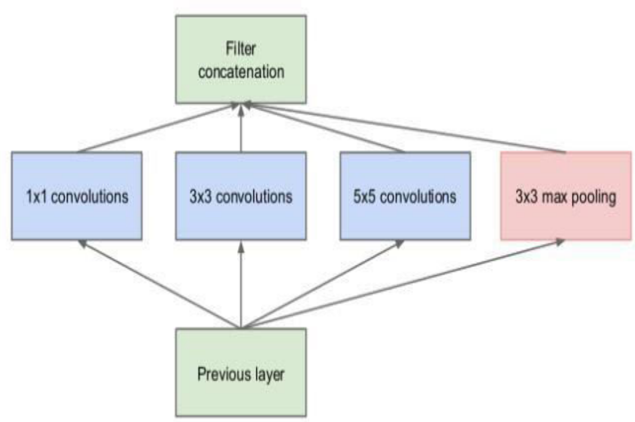

Fig2:Inceptionmodulenaïve

Fromtheabovefigure wegetthevariety of convolutionsthatwe wantspecifically,we willbe using1×1,3×3,and5×5convolutionsalongwitha 3×3maxpooling. If you'rewonderingwhatthe maxpooling isdoingtherewithalltheother convolutions,we'vegotananswer:pooling isadded totheInceptionmodule for noother reasonthan, historically,good networkshaving pooling. The largerconvolutionsare more computationally expensive,sothepapersuggestsfirstdoing a1×1 convolution reducingthedimensionality ofits featuremap,passing the resultingfeaturemap througharelu,andthendoing thelargerconvolution (inthiscase,5×5or3×3).The1×1convolutionis key becauseitwillbeusedtoreducethe dimensionalityof its featuremap.

3.2 Tensorflow

Tensorflowis an open source machine learning library that came into existence since november 2015 which hasitsroot in Google brainteam.Itisa library usedfordoingcomplexnumerical computationtobuildmachinelearning modelsfrom scratch. Tensors, ingeneral, are simplyarrays of numbersorfunctionsthattransform accordingto certainrulesunderachange ofco-ordinates. Tensorflowisusedfor doinggraph based computations quickly. Nodes in thegraph represent mathematicaloperations,while the graph edges represent the multidimensional tensors communicated betweenthem. Pre-trained tensorflow modelsforsmalldeviceslikemobile,raspberrypi etcmakesit highly portable. Deep learningis heavily adoptedacrossmany companiesusing tensorflow.

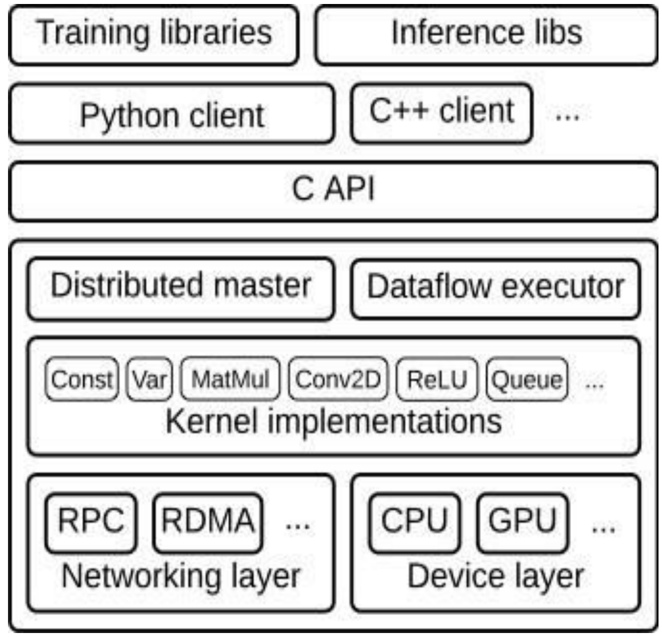

Fig3:Tensorflowarchitecture

As depictedintheabove figure tensorflowarchitecture consistsofclientwhichdescribes computationasa dataflow graphandinitiatesthe graphusingsession.Inasessionwecanperform allthenecessary computationsoftheclient.Inthe next leveldistributed masterPrunesaspecific subgraphfromthegraph,asdefinedby the argumentsto Session. Partitionsthe subgraphinto multiplepiecesthatrun indifferentprocessesand devices.Distributes thegraphpieces toworker services.Initiatesgraphpieceexecution byworker services.In the nextlevelthat isinkernel implementationswe performthecomputationsof individualgraphoperations.The devicelayer consistsofthe CPUandGPUthata system containsandnetworklayer consistof architectures likeRPC, RDMA.

3.3 Trainingand Testing

Inthisproject,wehavedividedthedatasetinto two folders manand woman each of which contains morethanhundredimagesinthemwhichwere used fortrainingandcrossvalidation.Wehaveachieved afinal test accuracyof 97.5 percentage.

3.4 Goals

The firstobjective inthe projectwastoensure that thetensorflowarchitecturewasfeasible.Withthe useofInception-V3modelandImageNetdataset, wehaveincresedtheaccuracyof prediction byusing cross entropyconsiderably.

3.5 Technical Details

Inthis section,we will discuss on thetechnical detailsofthenetworkarchitectureandhowwe have implemented and trainedit.

Softmax

Inthe currentarchitecture softmaxlayer ispresent whichcalculatesthelosswhichismadeproductive intheperiodoftraining andalsotheprobability during recognition.Someofthelosslayerslike multiclass SVM losstreatsoutputas class scores, softmaxtreatsthese scoresasunnormalizedlog probabilities of the classes. The softmaxfunction can bewritten as

$$f_j(z) = e^{Z_j} / \sum_k e^{z_k}$$

IV. DATASET

The dataset which is used for the purpose of training andtesting inthisproblemistheImageNet dataset which has derived from Inception-V3 modelz.For a normalhuman brainthe task of classifyinggender iseasy.However it isatough task for a computer toachieve the same. Eachimage is classifiedwithitsgender. Those pictureswere exposed todifferentnoises, angles and lighteffects thatwouldrepresenttherealworldconditions. The mostcommontype ofimage thatwasusedwasof frontal faces.Thefollowing figurerepresents few pictures of both thegenders in the dataset.

Fig4–Dataset

V. CONCLUSION

Despitehavingmany techniquestosolvegender classificationprobleminthe currentpaper we createdbasisfor theproblemofpredicting the genderwith tensorflowand inception modelwith an improvised accuracy.

Thevery challengingtaskinthisproblemwas establishing thetraining environmentto differentiate thedataintorespectivegenders,train them, cross-validate and merge the outcoming data intotestdata. Weanticipate the upcoming applicationsof thisprojecttosupport facial detection,enhance theperformance ofsocial networking sitesandalotofotherapplications. Eventually webelievethatthesupplementaltrain data wouldbeaccesible innearfutureinthe purpose ofgender classification that would permit prosperous methodsindifferenttypesof classification with largedatasetsthat would be implemented to this domain.

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