International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 08-14 www.ijaem.net ISSN: 2395-5252

Image fire detection algorithms based on convolution alneural networks

Pali Shivani Yogesh[1], Prajapati Krish Prakash[2], Rayewar Aditya Santosh[3], Sonyalkar Anirudh Shrishail[4]and Mali Shital[5]

[1,2,3,4]*Student, Department of Electronics and Telecommunication Engineering, RamraoAdik Institute of Technology,*

Nerul[5]*AssistantProfessor,DepartmentofElectronicsandTelecommunicationEngineering,RamraoAdikInstituteofTechnology,Nerul*

Submitted: 01-05-2022 Revised: 04-05-2022 Accepted: 08-05-2022

ABSTRACT. Detecting smoke and fire is challenging due to the great range ofcolour and texture in visual environments. To address this issue, a number ofsmokeandfirepictureclassificationsystemshavebeenproposed;nevertheless, the bulk of them rely on rule-based approaches or handcraftedattributes.Asanewfiredetectiontechnology,imagefiredetectionhasrecently played a key role in reducing fire losses by warning users early in thecase of a fire. Based on SSD's powerful object recognition CNN models andYOLOv3,thisstudyprovidesnovelimagefiredetectionapproaches.Accordingtoacomparisonofproposedandcurrentmethodologies,The fire detection algorithm based on the object detection CNN is more accurate than other algorithms. In particular, the average accuracy of the YOLO v3-based method is 83.7%, which is higher than other available algorithms. In addition, YOLO v3 has improved the robustness of detection performance and increased the detection speed to 28 frames per second. It meets the real-time detection requirements.

Keywords:-SSD,YOLOv3,CNN,Fire detection,Image

I. INTRODUCTION

Withfasteconomicexpansion,thevolumeandcomplexityofstructureshasgrown,posingsignificant fire-fighting issues. To limit fire losses,early fire detection and alarm with high sensitivityand accuracy are required. Traditional fire detectiondevices, such as smokeand heat detectors, areineffectiveinhugeexpanses,complicatedbuildings ,or areas with a lot of noise. Missed detections, falsealarms,detectiondelays,andotherissuesarecommonduetothelimitsofaforementioneddetectionmethods,Increasingthedifficultyofreceiving early fire alerts. The detection of imagefires has lately been a popular research topic. Benefits of this technology include early fire detection, precision, flexible system installation, and the ability to reliably detect fires in large spaces and complex building structures. An algorithm is used to interpret the visual data from the camera to detect the presence of a fire or fire hazard in the photo. Therefore, the detection algorithm is at the heart of this technology and directly determines the performance of the image fire detector.Image preprocessing, feature extraction,andfiredetectionarethethreemainstepsofpicture fire detection. One of the most significantcomponentsofalgorithmsisfeatureextraction.Manual fire feature selection and machine learningcategorizationareusedintheconventionaltechnique.Calculations have the detriment of requiring master information to pick human highlights. Regardless of the way that the analysts embrace various assessments into the picture elements of smoke and fire, they just uncover essential picture parts.

Due to the type of fire and the complexity of the scene, and the large number of interference events that occur in real-world applications, algorithms that extract low-complexity and medium-complexity image features are like fire and fire. It is difficult to distinguish, resulting in precision and weak generalization capabilities.

II. LITERATURE SURVEY

[A] Comparativestudyofmodernconvolutional neuralnetworksforsmokedetectiononimagedata
A. Filonenko, L. Kurnianggoro, K. Jo proposed amethod to evaluates modern convolutional neuralnetworks (CNN) for the task of smoke detection onimagedata.ThenetworksthatweretestedareAlexNet, Inception-V3, Inception-V4, ResNet, VGG,andXception.Theyallhaveshownhighperformanceonhuge ImageNetdataset,butthepossibilityofusingsuchCNNsneededtobechecked for a very specific task of smoke detectionwith a high diversity of possible scenarios and asmall available dataset. Experimental results haveshownthatinception-basednetworksreachhighperformance when samples in the training datasetcover enough scenarios while accuracy dramaticallydropswhen oldernetworksare utilized.

[B] A Deep Normalization and Convolutional NeuralNetworkforImageSmokeDetectionZ.Yin,B. Wan, F.YuanandcolleaguessuggestedSmokerecognition from photographsisdifficult owing tothe wide range of smoke color, texture, and forms.There have been some suggested smoke detectiontechnologies,howeverthemajorityofthemarebasedonhand-craftedcharacteristics.Wepresentauniquedeepnormalizationandconvolutionalneuralnetworktoincreasesmokedetectionperformance.(DNCNN)with14 layerstoimplementautomaticfeatureextractionandclassification.Traditionalconvolutionallayersarereplaced by normalization and convolutional layersin DNCNN to speed up the training process andimprove smoke detection performance. We apply anumber of data augmentation strategies to produceextra training samplesfrom original training datasets to prevent overfitting caused by unbalancedandinadequatetrainingsamples. Onoursmokedata sets, our technique obtained exceptionally lowfalse alarm rates of less than 0.60 percent, withdetectionratesexceeding96.37 percent.

[C] ConvolutionalNeuralNetworkArchitecture VariantsforNon-TemporalReal-TimeFireDetectionDefinedExperimentallyT.P.Breckonand A.J.DunningssuggestedWeexaminehowtoautomatically locate fire pixel patches in video (orstill)imageswithinreal-timeconstraintswithoutrelying on temporal scene information in this paper.Weinvestigatetheperformanceofempiricallyconstructed,lowercomplexitydeepconvolutionalneural network designs for this job as a follow-up topreviousworkinthefield.Weinvestigatetheperformanceofempiricallyconstructed,lowercomplexitydeepconvolutionalneuralnetworkdesigns for this job as a follow-up to previous workinthefield.Incontrasttocurrentindustrytrends,our study shows that a network architecture withmuch reduced complexity may reach a maximumaccuracyof0.93forwholepicturebinaryfire detection, with 0.89 accuracy inside our super pixellocalization framework. These simplified structuresalsoprovidea3-4-foldgainincomputationalperformance,allowingforupto17framespersecondprocessingonmodernhardware,regardlessof temporal information. To demonstrate maximumrobust real-time fire zone identification, we exhibittherelativeperformanceattainedvspastworkusingbenchmarkdatasets.

[D] Fire Detection Convolutional Neural Networkwith Multi-ChannelsW.Mao,W.Wang,Z.Dou,and Y.LiarguedthatfirerecognitionmethodshavegottenalotofattentionintheacademiaandIndustry in recent years. Sensor-based identificationalgorithmsnowrelysignificantlyonexternalphysicalsignals,whichwillmostlikelylowerrecognitionprecisioniftheexternalenvironmentchanges drastically. With the fast advancement ofhigh-definitioncameras,technologiesbasedonvisual feature extraction give another solution forpatterndetectioninvideosurveillance.However,duetotwoflaws,thesesystemscouldnotbeextensively and successfully used to fire detection.There are too many interference elements in theroom or tunnel, such as lamplight and automobilehighlight,whichwillcausethesignaltobedisrupted. The characteristics are heavily reliant onexisting knowledge of flame and smoke, andthereis no uniformand automated extraction approachfordifferentfirescenarios.Deeplearning,asa breakthrough in pattern recognition, is capable ofextracting usable informationfromrawdata.

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 08-14 www.ijaem.net ISSN: 2395-5252

candeliverreliablerecognitionresultsautomatically. To address the shortcomings notedabove,thisresearchproposesauniquefirerecognitionapproachbasedonmulti-channelconvolutionalneuralnetworks,whichisbased onthedeeplearningnotion.First,threechannelcolourfulpicturesarecreatedastheinputforaconvolutional neural network; second, hidden layerswithmultiple-layerconvolutionandpoolingarecreated, and model parameters are found modifiedviaback propagation.

III. PROPOSEDMETHODOLOGY

The main purpose of this projectis to create anearly fire detection system. There are no works onpicturealgorithmicanalysisthatIamawareof.Commondetectionalgorithms,suchasmanuallyand automatically extracting image features, haveloweraccuracy,delayeddetection,andalargeamountofcomputation,whichcanresultinhazardousevents andthusposeathreattohumans,animals,andnaturein generalinthecurrent state of the environment. A fire detectionsystem is necessary to address all environmentalproblemsbydetectingfireearly.Aconvolutionalneuralnetworkisusedtocreate thissystem(CNN).

The object detection method is used to build the flow of an image fire detection system based on a convolutional neural network. The cognitive CNN performs region suggestion, feature extraction, and classification. Tobegin,theCNNusesconvolution, pooling, and other techniques to createregionsuggestionsfromapicture.The area-based object identification CNN then uses a convolution layer, a pooling layer, a fully connected layer, and a normalization layer to identify the presence or absence of a fire in the proposed area. The convolutional layer is in the center of the CNN. Unlike other brain networks thatuse association loads and weighted aggregates, theconvolutionallayercreateshighlightguidesofuniquepicturesusingpicturechangechannelscalled convolution portion. The convolutional layerconsists of a collection of convolution sections. To create an element card, cleavage slides on the picture and handles another pixel through a weighted pixel that hovers.For the first image, the element map reflects theelementsofaviewpoint.

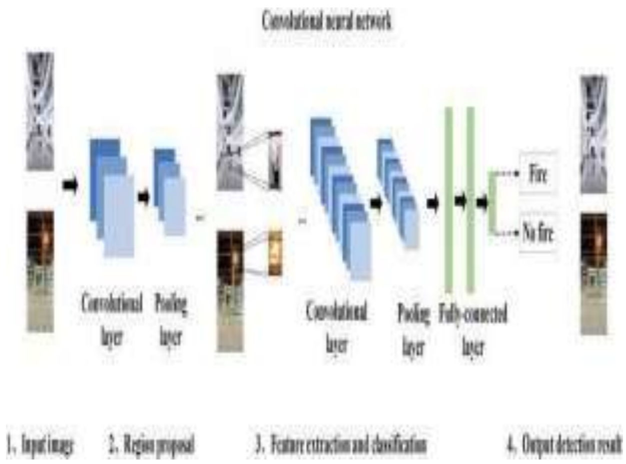


Figure1:Firedetectionalgorithmsbasedondetection CNNs

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 08-14 www.ijaem.net ISSN: 2395-5252

The Equation which calculationformulafortheconvolutionlayeris
$\Sigma_{j-1}\Sigma_{i-1}$

networks extract increasingly complicatedcharacteristics.Asaresult,obtainingcomplicatedpictureinformationnecessitates the use of a deep network.The featureextraction networksused inthis article are Inception Resnet V2 andDarknet-53,whichhave235and53

y= j=0 **w** **ij** i=0 **x** m+1,n+**j**
≤N)
+b,(0≤m≤M,0≤n
convolutionallayersrespectively.

herexisaninformationpictureofasizeW×HandWmeansaconvolution bit of a size J×I and b indicateinclination and y means yield include maps.By and by, the worth of w and not set instonethroughpreparing.

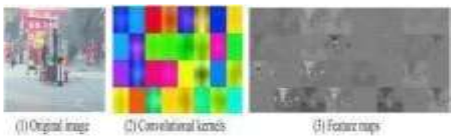


Figure2:Featuresextractedbythefirstconvolutionallayer

The 32 feature maps of a fire picturecreatedbythe32kernelsofthefirstconvolutional layer in Inception Resnet V2 (astate-of-the-artCNN).Therearethesamenumberoffeaturemapsandconvolutionkernels.Becausethislayerhasthreeconvolutionkernels,threefeaturemapsarecreated. The degree of activity is represented bythecolorofthepixels.Whitepixelsinthefeaturemapindicatepixelsintheoriginalimage that are strongly positively activated atthesamelocation.Stronglynegativeactivations are shown by black pixels. Thegreypixels showweakactivations.Thefeaturemapcreatedbythislayer'sconvolutional kernel 14 is active on edgeswhencomparedtotheoriginalpicture.Upper/loweredgesstimulatedark/lightareaspositively,whereasupper/loweredges activate light/dark areas adversely.Becausethe whiterpixelsinthemapcorrespondtoorangeportionsin theoriginal picture, the feature map formed bytheconvolutionalkernel26isactiveonorange pixels. It means that the kernels inthe earlier layers are mostly learning andextracting basic attributes such as colour,edges,andsoon.Whensceneriesarecomplicated, as well as many interferenceoccurrences,basicfeaturescannotidentify fire and disturbance, according tothese feature maps. Therefore, we need an image-based fire detection algorithm that can extract complex image features to detect fires under real-world conditions. This is where deep convolutionalneural networksexcel.

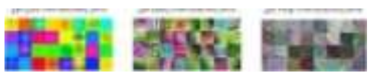


Figure3:Samplesofkernelsinsomeconvolutionallayers.

kernelexamplesfromInceptionResnetV2'sfirst,third,andsixthconvolutionallayersIt means thatinlater levels,the

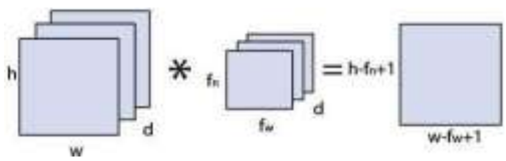
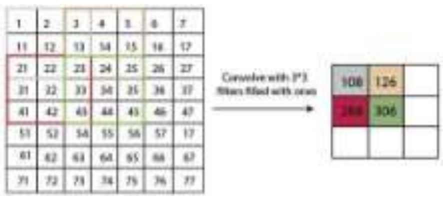


Figure4:Caption

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 08-14 www.ijaem.net ISSN: 2395-5252

A math operationthat takes two inputs,such as an image matrix and a kernel orfilter. Thedimensionoftheimagematrixish×w×d.Thedimensionofthefilterisfh×fw×d.Thedimensionoftheoutputis(h-fh+1)× (w-fw+1)×1.
Stride is the number of pixels shiftedacrosstheinputmatrix.Ifthestepsizeis1,the filter is moved by 1 pixel at a time, andif the step size is 2, the filter is moved by 2pixelsatatime.Thefollowingfigureshowsthatconvolutionworksinincrementsof2.

Figure5:Stride



Padding is the addition of (typically)0-valuedpixelsonthebordersofanimage.This is done so that the border pixels are notundervalued(lost)fromtheoutputbecausethey would ordinarily participate in only asingle receptive field instance. Padding istypically set to the kernel dimension -1. Soa3x3kernelwouldreceivea2-pixelpadonall sidesof theimage.

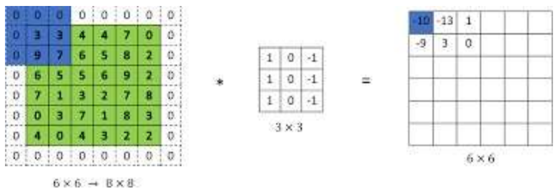


Figure 6: Applying padding of 1 before convolving with3×3filter

ThepoolinglayerisanotherimportantconceptofCNN,whichisaformofnonlineardownsampling.Thereareseveralnon-linearfunctionsforimplementingpooling,butthemostcommon is maximum pooling. Divide theinputimage intoaseriesofrectanglesand divide each of these sub-regions outputsthemaximum.

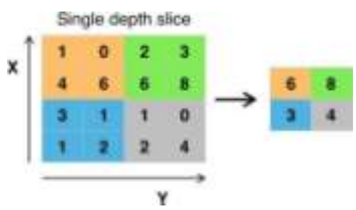


Figure7:Maxpoolingwitha2x2filter andstride=2

Theactualplacementofafeature,onthe surface, appears to be less relevantthan its estimatedlocation in relation toother features. This is the basis for poolinginconvolutionalneuralnetworks.Bygradually lowering the spatial dimension oftherepresentation,thenumberofparameters,memoryfootprint,andamountof computation in the network, the poolinglayeraidsinthemanagementofoverfitting.Thisisknownasdown-sampling.Apoolinglayerisusuallyplacedbetweeneachconvolutional layer in a CNN architecture(eachofwhichisoftenfollowedbyanactivation function, such as a ReLUlayer). Ina CNN, pooling layers contribute to localtranslation

International Journal of Advances in Engineering and Management (IJAEM)
Volume 4, Issue 5 May 2022, pp: 08-14 www.ijaem.net ISSN: 2395-5252

invariance, but global translationinvarianceisnotachieveduntilglobalpooling is added. The pooling layer spatiallyresizes the input and operates separately oneach depth, or slice, of the input. A layerwithsize22filtersandastrideof2subsamples each depth slice in the inputby 2 along both width and height, deleting75 of the activations, which is a commontypeofmax pooling.
Inthiscircumstance,everymaximumoperation is greater than four digits. Thedepthdimensionisnotchangedinanyway (this is true for other forms of poolingas well). Other than max pooling, poolingunitscanusefunctionslikeaveragepoolingor2-normpooling.Averagepoolingusedtobepopular,butit hasrecently fallen out of favour in favour ofmaximum pooling, which is more practical.There has been a recent tendency towardusingsmallerfiltersorskippingpoolinglayerscompletelyduetotheconsequences of fast spatial decrease ofthesizeoftherepresentation.
ROI is being pooled into a 2x2 grid. In thisexample, the region recommendation (aninput parameter) is 7x5. Pooling in whichthe output rectangle is a parameter andtheoutputsizeisfixedisknownas"RegionofInterest"pooling(alsoknownasRoIpooling).Poolingisacriticalcomponentofconvolutionalneuralnetworks for object detection based on theFastR-CNN[68]architecture.
LayerthatiscompletelyinterconnectedThefinalclassificationisdoneusingfullyconnectedlayersaftermultipleconvolutionalandmaxpoolinglayers. In normal (non-convolutional) artificialneural networks, neurons in a fully connectedlayer have connections to all activations intheprecedinglayer.Asaresult,them activations may be calculated as an affinetransformation, with matrix multiplication andabiasoffset(vectoradditionofalearnedorfixedbias term).

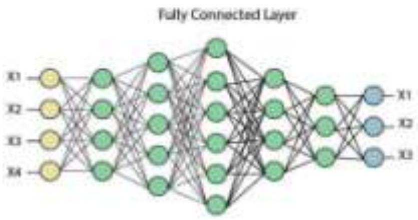


Figure8:Fullyconnectedlayer

IV. RESULT ANALYSIS

Thegoalofourprojectwastocreatearobustprogrammed that can detect fire in photosand work in any situation. In this regard, wetestednumerousconvolutionalneuralnetworksforimplementation,suchasyolov3and ssd, and found that they provided theseperformancemetricvalues(Accuracy,Precision and Recall values for this was ancombinationof75percentto85percentrespectively).Ourapplicationisattractive,resilient,andreliablewhencomparedtotraditional hardware solutions, and it givesexcellentperformancewithouttherequirement for a specialized infrastructure.Our model is easy to construct, modify, andupgradesinceitusesdeeplearningandtransferlearning approaches. It also usesfewercomputationalresourcesandperformsbetter than existing software solutions thatrelyheavilyonfeatureengineeringanddomainknowledge.


Figure9:-Result

V. CONCLUSION

To improve the performance of image firedetection technologies, the advanced objectidentification CNNs of SSD and YOLO v3 areusedtodevelopimagefiredetectionalgorithms. Thealgorithmsproposedcanautomaticallyextractcomplex imagefireattributes and consistently identify fire in arangeofsettings.

VI. FUTURE SCOPE

Theapplicationmightbeimprovedbyusing a larger dataset of fires in variousphasesanddimensionstotrainthemodel. With greater GPU power, we may be abletodeploytwodeeplearningmodelsforfeatureextraction,concatenatingandcategorizingtheiroutputfeaturevectorsfor improved robustness. To achieve firelocalization and classification, an R-CNNmodel can be utilized. More sophisticateddeep learning architectures with enhancedfeature extraction are expected to developinthefuture.Whenperformedonmachineswithmoreprocessingpowerthan the one on which it was written, theapplicationwillperformsignificantlybetter.

REFERENCES

[1] K.Muhammad,J.Ahmad,I.Mehmood,etal., Convolutional neural networks based firedetectioninsurveillancevideos,IEEEAccess 6(2018)18174–18183.

[2] C.Tao,J.Zhang,P.Wang,Smokedetectionbasedondeepconvolutionalneuralnetworks,in:2016InternationalConferenceonIndustrialInformatics-ComputingTechnology,IntelligentTechnology,IndustrialInformationIntegration(ICIICII), 2016,pp.150–153.

[3] A.Filonenko,L.Kurnianggoro,K.Jo,Comparative study of modern convolutionalneuralnetworksforsmokedetectiononimage data, in: 2017 10th InternationalConference on Human System Interactions(HSI),2017,pp.64–68.

[4] Z. Yin, B. Wan, F. Yuan, et al., A deepnormalizationandconvolutionalneuralnetwork forimage smoke detection, IEEEACCESS5(2017)18429–18438.

[5] A.J.Dunnings,T.P.Breckon,Experimentally defined convolutional neuralnetworkarchitecturevariantsfornon-temporalreal-timefiredetection,in:201825th IEEE International Conference onImage Processing (ICIP), 2018, pp. 1558–1562