Classification Of Satellite Images Using Deep Learning

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ABSTRACT— Satellite photos are widelyusedinfieldsincludingemergencymanagement,security,andenvironmentalmonitoring.Thesegoalscan'tbeachievedwithout the help of humans and the ability toproperlyidentifyobjects.Withsomanypossiblesearchspaces and so few analystson hand, automation is essential. However,owingtotheirfocusonaccuracyandprecision,conventionaltechniquestoidentifyitemsandcategorizationareconstrainedintheircapacitytodeliverasolution.Automatingthesestepsusingsupervised neural class ML algorithms hasshownsomesuccess.Thereissomeevidence that convolutional neural networks,akindofartificialneuralnetwork,mayenhancebothpictureidentificationandunderstanding. In this case, we use them tolearnhowtoidentifyartificialfeaturesinhigh-resolution,multispectralsatelliteimagery.Weprovideadeeplearningapproachtoclassifyingfeaturesor architecture into 63 categories utilizing theIARPAFunctionWorldMap(fMoW)dataset.Convolutionalalongwithotherartificialneuralnetworkscomprisethefoundation of the system, which integratesvisualinformationandsatellitedata.Itiswritten in Python and uses the TensorFlowand Keras deep learning frameworks; it runson a Linux server that has a Geforce Titan Xinrealitygraphicscard.Thissystemispresentlyrated#2inthefMoWTopCodercompetition. 15 of 16 classes are correctlyidentified (with 95% confidence or better),giving it an F1 score of 0.797 and a totalaccuracyof83%.

INTRODUCTION

Deep learning machine learning models areabletogeneralizedatabybuildingabstractions on top of each other in the formoflayeredrepresentations.theimpressiveresultsinobjectrecognitionandclassificationmightbeexplainedbythe integrationofpowerfulGPUswithlarge-scale neural network models, or deep neuralnetworks(CNNs).Objectrecognitionand classification in photos is the focus of theImageNetworkLarge-ScaleVisualRecognitionCompetition,whichhasbeenwon by CNN-based algorithms every yearsince 2012. As a direct consequence of thisinnovation in visual interpretation, some ofthe top web firms have already created itemsandservicesbasedonCNN.Therearenumerouslevelsofprocessinginа CNN.Theimageisprocessedviamanyconvolutionfiltersatdifferenttimes.Advanced feature detectors are available athigherlevels,andtheymayatfirstlookresembleFig.1'scolorblob/Bag-of-visualfilters.Bycombiningthesensorreadings in the last "dense" layer of a fullyconnectedCNN,asetorposteriorprobability is generated, one for each class.In contrast to earlier methods like SIFT andHOG,CNNsmaybetaughtsansthenecessity forthealgorithm'screatortomanuallydevelopfeaturedetectors.Thenetwork figures out for itself during trainingwhichtraitsarecrucialandhowtorankthem. The firsteffective CNNs had fewerthantenlayersandwerefirstcreatedfordecipheringhandwrittenZIPcodes.Incomparisonto LeNet'sfivelevels,AlexNet has eight. Since then, complexity has beensteadily increasing. Google debuted their 22-layer Inception model in 2015, and its 16-layer VGG model the year after. More layershavebeenaddedtonewerversionsofInception.Thereare152nodesintheResNet network, whereas DenseNet has 161.Withoutthecomputingcapabilitiesoftoday'sGPUs, these massive CNNs wouldbeimpossibletoimplement.Acceleratinggraphics processing units (GPUs) and open-source deep learning packages like Tensor &Kerashavespedforwardprogress.

RELATEDWORK

Uniquefeaturesoftheimagearehighlightedusingscale-independentlandmarks.

Thisresearchsuggestsamethodforaccurately matching severalcamera anglesof the same object or scene via extractinguniqueinvariantfeatures.Besidesbeinginvariant to picture scale and rotation, thefeatures have been shown to be resilient inmatching situations including varied degreesof affine deformation, 3D perspective shift,noisyintroduction,orvariationsinlight.Because each feature is unique, it may becomparedagainstavastlibraryofhigh-probability featuresextractedfromseveralphotos.Thispaperalsodetails amethodfor using these features in object recognition. Arapid nearest-neighbor approach is used tocomparetheitem'scharacteristicstoalibraryofknownobjectfeatures,andalowestsolutionwithconstantpostureparametersisusedtoverifytheobject'sidentification. This technique of identifyingobjects can distinguish things in near-real-timewithexcellentaccuracydespitethepresenceofnoiseandpartialobfuscation.

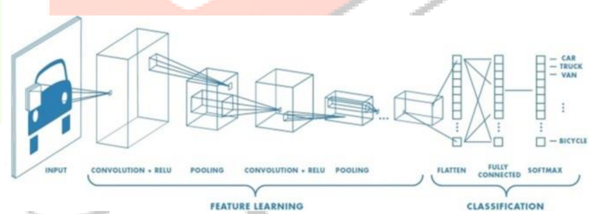
Trainingconvolutionalneuralnetworkstoclassifyimagesin ImageNet

Todothis,weusedahuge,powerfulconvolutional neural network to categorizethe one million high-resolution images thatmake up the Vascular cells ImageNet set fortraininginto1000groups.Onthetestingdata, our top-1 and top-5 tolerances of errorwere 39% and 18% less than the previousbest-practicevalues,respectively.Theneuralnetworkwithatotalof500,000neuronsconsistsoffive convolutionallayers, many layers that follow them, twolayersthatareconnectedglobally,andafinal linear softmax layer. We created a fast-learningconvolutionalnetworkwithnon-saturatinglayersandapowerfulGPUimplementation.Tosignificantlyminimizeoverfitting within the globally linked layers,we successfully used a novel regularizationmethod.

METHODOLOGY

Our deep learning algorithm categorized theitemsandinfrastructureinthefMoWdataset. In addition to a satellite image andotherdata,aboundingboxisenteredinto

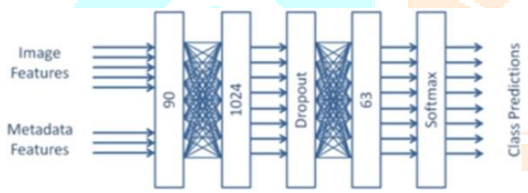
the system to determine the location of anitem.Itclassifiestheinformationinto63groups,amongwhichisknownas"falseidentification." Thesystemismadeupofconvolutionalneuralnetworks(CNNs),NNs,andseveralimageprocessingmethods.Join the data from the images withthefeaturesoftheCNNimages.Byaveraging the neural network (NN) outputswithout respect to relevance, the ensembleyieldspredictionprobabilityforthe63 classes.Maximum likelihood is used to maketheclassification.



KerasandTensorFlow,twodeep learningframeworks, were implemented in Python tocreate this system. The testing and trainingwere performed on CentOS Linux machineshousingGeforceTitanXgraphicsprocessingunits.Wewillnextbrieflysummarize the approaches we took to trainthesystemoncewehavediscusseditindetail.

A. Both the training and operational stagesof the system for machine learning use asinputs a satellite image and a bounding box

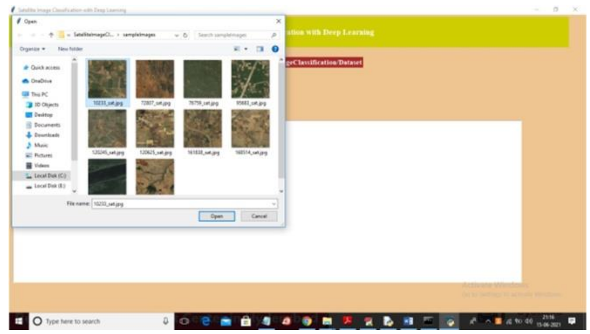
specifyingtheobjectorfacilitytoberecognized. The picture'sbounding boxisincreasedinsizebeforeanycroppingorresizing is done. We now give CNN its firstpixelcontexttoanalyze.Theaspectratioispreservedbysqueezingthesmallerdimensions into the larger one, making theenclosingboxsquare.(Byusingthesquaringmethod, we found that certain CNNs faredbetter than others.) The image is then scaledand cropped such that the bounding box isinsidetheCNN'sfieldofview.

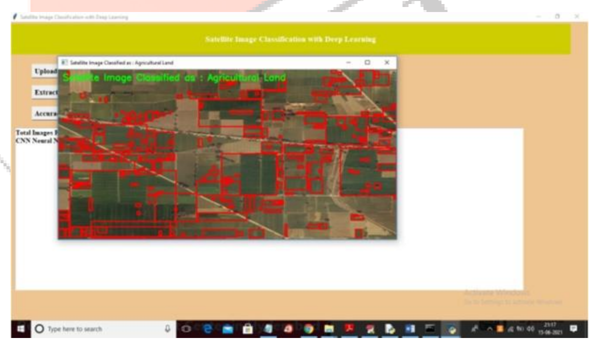


B. Asatellitepicture&aboundingboxdescribing the item or facility that has beenidentifiedareusedasinputsinboththetraining & operational phases of the machinelearning system. Before further cropping orscaling is done, the image's bounding box isexpanded. We are now providing CNN withitsinitialpixelcontextforanalysis.Thesmaller dimensions are compressed into thebiggerone,creating asquarebox,whichmaintainstheoriginal aspectratio.(Thesquaring technique allowed us to determinewhich CNNs performed best.) The picture isthenresized&trimmedsuchthattheperimeterfalls inside the region of interestoftheCNN.

RESULTANDDISCUSSION

Hereweareuploadingdatasetandtrainthealgorithm.Hereweareclassifytheimage.





CONCLUSION

Wehaveshowntheabilityofadeeplearning system to recognize and categorizefeatures present in excellent quality multi-spectralsatelliteimagery.Thesystemis formed up of a collection of convolutionalneuralnetworks(CNNs)thatevaluatesatellitedataandmakepredictionsusingsu pplementaryneuralnetworks.Overamillioni magesfromtheIndependentevaluation fMoW dataset, including the falsealarmclass,thesystemachievesanefficiency around 0.83 and an F1 measure of0.797.Itachievesasuccessrateof95%orabovein15classes,whichisanimprovement of 4.3% over the John HopkinsUniversityAPLmodelinthefMoWTopCodercompetition.Usingthistechnology, we can search through massivevolumes of satellite imagery using a detectorin search of potentially significant locations.Thismighthelpanswersomeofthequestions that have been raised regarding theinquiry thus far. Rescue workers might usethe database to predict the effects of stormsasmudslides,policecoulduseittofindunlawfulminingactivities,andinvestorscould use it to maintain tabs on agriculturaldevelopmentinadditionoil welldrilling.

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