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Overview on remote sensing image scene classification using deep learning

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***Abstract*---**Now a days, deep learning is becoming very famous dueto its power fulability of learning. Deep learning has been applied for remote sensing image analysis tasks including scene classification. Remote sensing has seen an enormous increase in the enhancement of digital images captured from satellites that cover almost all angle of the surface of the earth. This growth in data has forced the community of the remote sensing to apply deep learning algorithms to solve different remote sensing tasks. Convolutional neural networks have obtained huge success in the field of scene classification. The current best scene classification approaches are still far from achieving the human's ability to classify scene types with a few labelled samples. This study provides a systematic survey of deep learning methods for remote sensing image scene classification by covering mover than 9papers.Inthispaper, we provide a brief discussion on Convolutional neural networks. Here we also discussed few-shot learning algorithm to overcome the gap between the current understanding level of machine and human-level performance.

***Keywords*---**Deeplearning, Convolutional Neural Network, Few-shotlearning, Training sets.

Introduction

Deepleaningisabranch ofmachinelearningwhich inturn a branch of an artificial intelligent. It is implemented withthehelpofNeuralNetworks,andtheideabehindthemotivation of Neural Network is the biologicalneurons, whichisnothingbutabraincell.RemoteSensingisatechniqueusedtocollectdataabout

theearthwithouttakingphysicalsampleof the earth's surface. This technology is used innumerousfieldslikegeography,hydrology,ecology,oceanography,glaciology,geology, etc.
Inthissection,weprovidedabriefdiscussiononConvolutionalneuralnetworks.Theres tofthepaperisorganizedasfollows.Literature review section,discussesthesystematicliteraturesurveyondeeplearningmethodsforremote sensing imagesceneclassificationbycovering9researchpapers.Abriefintroductionandworking offew-shotlearningwithexample is provided in Proposed word. Finally, weconclude thisarticleinConclusion.

Deeplearningmodels:

1. Deepbeliefnetworks(DBNs)
2. Auto-encoders
3. Stackedauto-encoders
4. Convolutionalneuralnetworks(CNNs)
5. Generativeadversarialnetworks(GNNs)
6. Recurrentneuralnetworks(RNNs)

ConvolutionalNeuralNetworks:

Convolutionalneuralnetworks,alsoknownasCNNs,area special form of neural network designed for processing datathat has a known grid-like representation, for example imagedata, which can be considered a two-dimension (2D) grid ofpixels. CNNs are a kind of multilayer network with learningability that consists of convolutional layers, pooling layers, andfullyconnectedlayers.

Convolutionallayers:
Theselayersareusedforfeatureextraction fromimages.

Pooling layers: These layers are to execute a max or averageoperation over a small area of each input feature map, poolinglayersareappliedbetweentwosuccessiveconvolutionallayers.

Fullyconnectedlayers: These layers areusuallyappearedinthetoplayerofCNNs,whichcansummarizethefeaturesextracted fromthebottomlayers.

Softmax layer: The SoftMax classifier is used to normalize thefully connected layer output between 0 and1. It is basicallyusedtoidentifytheoutputwithhighestprobability.

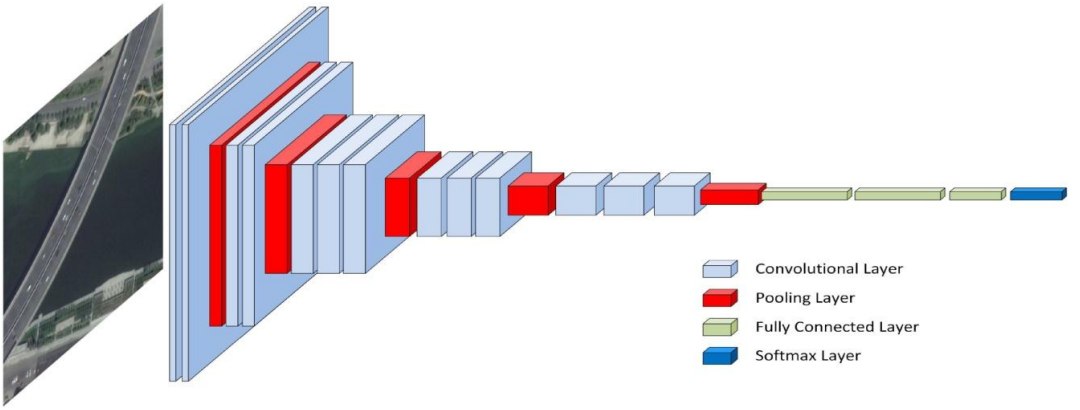

Fig 1: *Convolutional Neural Network*

Literature review

LazharKheliftetal.intheyear2020introducedthefundamentals of deep learning methods which are frequentlyadopted for change detection. This paper concentrates on deeplearningchangedetectionapproachesforremotesensingimagesbyprovidingageneraloverviewoftheexistingmethods[1].

Intheyearof2020,GongChenget al.discussedthechallenges,Methods,Benchmarks,andOpportunitiesforRemoteSensingImageSceneClassification.Inthispaper,authorsweresurveyedthreekindsofdeep learning-basedmethodsindetailandintroducedthemainstreamsceneclassification benchmarks[2].

Hamid Ghanbariet al.in 2021, they discussedameta-analysisof416peerreviewedjournalarticles,summarizesConvolutional Neural Networks advancements, and its currentstatus underremotesensingapplications[4].

Lei Ma et al.in 2019,authorscovernearly every applicationandtechnologyinthefieldofremotesensingusingdeeplearning.Themajor Deeplearningconceptspertinenttoremote-sensingareintroduced[5].

DanfengHonget al.in2020,theyshowdifferentfusionstrategies as well as how to train deep networks and build thenetwork architecture. Specifically, five fusion architectures areintroduced and developed, further being unified in our MDLframework [3]

Gong Cheng et al.in 2016,introduced adeep convolutionalneuralnetwork(CNN)basedsceneclassificationmethod,whichadopted theexistinghigh-capacityCNNmodelstoextractmorericherhigh-levelimagerepresentationfeatures[7].

Gong Cheng et al. in 2019, they have tackled the problem ofHRSSsceneclassificationusingasmallpoolofunlabelledimages and only a few labelled images per category, namely,few-shotsceneclassification(FSSC),whichismorechallengingthancommonsceneclassification task[6].

Fengpenget al.in 2020,Akey regionorlocationcapturingmethodcalledkey filterbank(KFB),Thismethodcancombinewithdifferent CNNmodels to improve the performance of HRRS imagery sceneclassification[8].

DalaAlajaji,et al.in 2019, explained the deep few-shot learning methodfor classification of Remote Sensing image under the N-wayfew-shotlearningscenario.Theproposedmethodusedonprototypical deep neural networks which was combined withpre-trainedconvolutionalneuralnetwork[9].

M.E. Paoletti, et al. in the year of 2017, the authors present anewconvolutionalneuralnetworksarchitectureforthe classification of hyperspectral images. The proposed CNN is a3-Dnetwork that usesbothspectralandspatialinformation.Theresultsindicatethattheproposednetwork performs accuratelyandefficientlywhencomparedwithothertraditionalArtificialneuralnetworks[16].

In the year 2017, Xingrui Yu et al., introduced a basic dataaugmentationoperationtoaddressthefundamentaldatalimitationprobleminapplyingdeeplearningforremotesensingimageprocessing.Toimprovetheremotesensingsceneclassification performanceofConvolutionalneuralnetworks,theauthorshasdescribedhowtousedataaugmentation[14].

QingWangetal.intheyearof2018,introducedafasterregion-basedconvolutionalneuralnetworks(FasterR-CNN)forthedetectionofhigh-resolutionremotesensingimagechange. Faster R-CNN method Achieve higher accuracy andkappacoefficient[17].

Table1
Literature Review

S.no	Authors	Title	**Focusofpaper**
1	Lazhar Khelift, Max,Mignotte.	DeepLearningforChangeDetectioninRemoteSensingImages: ComprehensiveReviewandMeta-Analysis.	Inthispaper,theauthorshaveintroducedthefundamentalsofdeeplearningmethodswhicharefrequentlyadoptedforchangedetection.
2	GongCheng,XingxingXie, Junwei Han, Lei Guo,Gui-Song Xia.	RemoteSensingImageSceneClassificationMeetsDeepLearning: Challenges,Methods,Benchmarks,andOpportunities.	Inthispaper,authorsdiscussedthechallenges,Methods,Benchmarks,andOpportunitiesforRemoteSensingImageSceneClassification.
3	HamidGhanbari,MasoudMahdianpari,SaeidHomayouni,FaribaMohammadimanesh.	AMeta-AnalysisofConvolutionalNeuralNetworks forRemoteSensingApplications.	In this paper, author discussed a meta-analysis of 416 peer reviewed journal articles, summarizes Convolutional Neural Network advancements, and its current status under remote sensing application.
4	LeiMa,Yu Liu,XueliangZhang, Yuanxin Ye, GaofeiYin,BrianAlanJohnson.	Deeplearninginremotesensing applications:A meta-analysisandreview.	In this paper, authors cover nearly every applicationand technology in the field of remote sensing usingdeeplearning.
5	Danfeng Hong, LianruGao,NaotoYokoya,JingYao,JocelynChanussot,QianDu andBing Zhang.	MoreDiverseMeansBetter:MultimodalDeepLearningMeetsRemote-SensingImageryClassification.	It shows different fusion strategies as well as how totraindeepnetworksandbuildthenetworkarchitecture.Specifically,fivefusionarchitecturesare introduced anddeveloped,furtherbeing unifiedinourMDL framework.
6	GongCheng,ChengchengMa, Peicheng Zhou, XiwenYao,JunweiHan.	SceneClassificationofHigh-ResolutionRemoteSensingImageUsingConvolutionalNeural Networks.	Inthispaperauthorsintroduced adeepconvolutionalneuralnetwork(CNN)basedsceneclassificationmethod,whichadoptedtheexistinghigh-capacityCNNmodelstoextractricherhigh-levelimagerepresentationfeatures.
7	GongCheng,XingxingXie, Junwei Han, Lei Guo,Gui-Song Xia.	Sceneclassificationofhigh-resolutionremotesensingimagesviaself-placeddeeplearning.	Tackling the problem of HRSS scene classificationusing a small pool of unlabeled images and only afew labelled images per category, namely, few-shotsceneclassification(FSSC), whichismorechallengingthancommonsceneclassificationtask.
8	FengpengLi,RuyiFeng, WeiHan,andLizheWang.	High-ResolutionRemoteSensingImageSceneClassificationviaKeyFilterBankBasedonConvolutionalNeuralNetwork.	Akeyregionorlocationcapturing methodcalledkeyfilterbank(KFB),Thismethodcancombinewithdifferent CNNmodelstoimprovethe performanceofHRRSimagerysceneclassification.
9	DalaAlajaji,HaikelS.Alhichri,NassimAmmour,NaifAlajlan.	Few-ShotlearningforRemoteSensingSceneClassification.	In this paper, authors explained the deep few-shotlearningmethodforclassificationofRemoteSensingscenes.

Proposed Work

This paper proposed to use few-shot learning method forscene classification. Few-shot learning is a meta-learning. Thismodelhaslearnedthesimilarityanddifferencebetweenobjects. The idea is to train a function that predicts similarity.The major goal is not to let the model recognize the images inthe training set and then generalize to the test set instead, thegoal is to learn. The proposed model shown infigure2, whichisfurtherexplainin theexample.

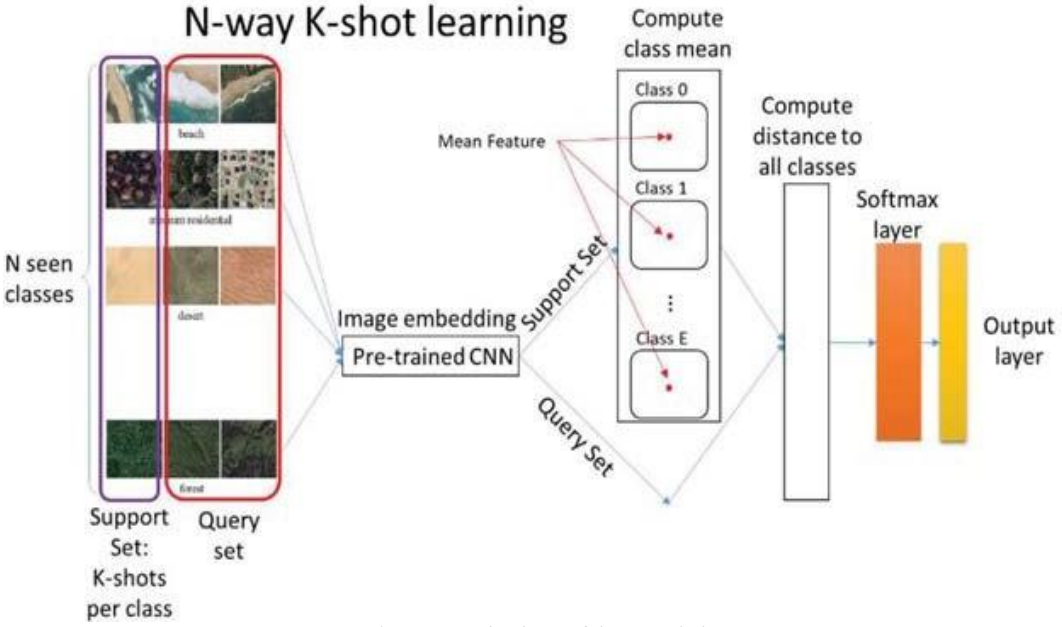

Fig2: WorkFlowofthemodel

Forexample,thetrainingset(Fig3.)doesnothaveafootballfieldclass,sothemodeldoesnotknowthatthequery sample(Fig4.).Weneedtoprovidethemodel withmoreinformation.Wecanshowthecardstothemodel.Everycardhasanimageandaname.Thesetofcardsisknownassupportset(Fig5).

Fig3: Trainingsetsample

By comparing the query with the cards, the model finds thequerymostsimilartothefootballfield.So,themodelpredictsthatthequeryisafootballfield.

Fig4: Querysample

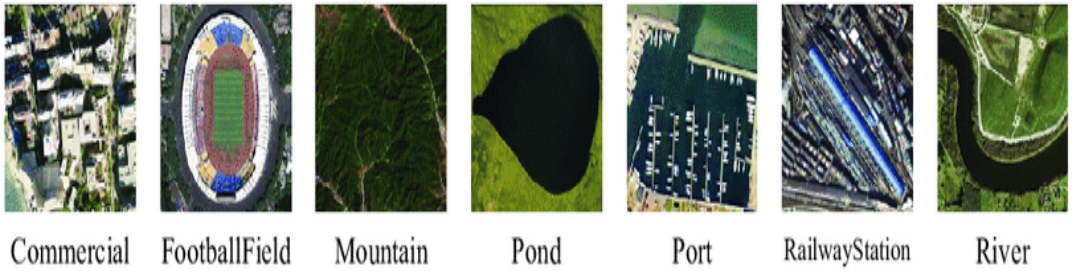

Fig5: Supportset

Terminologies of few-Shot learning

Wayandshotareterminologiesoffew-shotlearning are:

a) K-way:thesupportsethaskclasses.
b) N-shot:everyclasshasnsamples.
c) Infig.6,Kis6,Nis3.Therefore6-way3-shot.

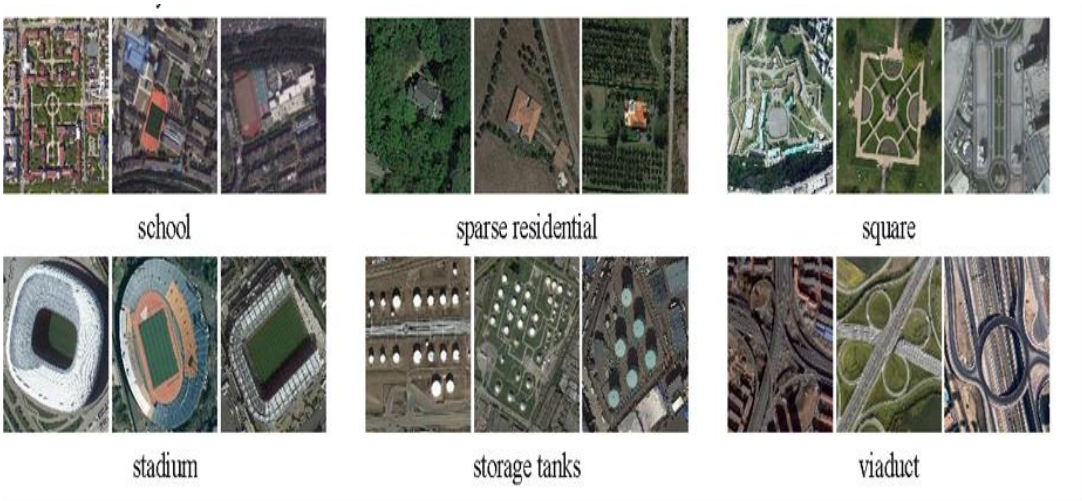

Fig6: Supportset

Similarity function

a) Thebasicideaoffew-shotlearningistotrainafunctionthatpredictssimilarity.
b) Similarityfunctioncanbedenotedbysim(x,x')(figure7).
c) sim(x1,x2)=1,sim(x2,x3)=0,sim(x1,x3)=0(figure7).
d) First,learnasimilarityfunctionfromalarge-scaletraining dataset.
e) Similarityfunctioncanbeusedaftertrainingformaking predictionforunseenqueries.

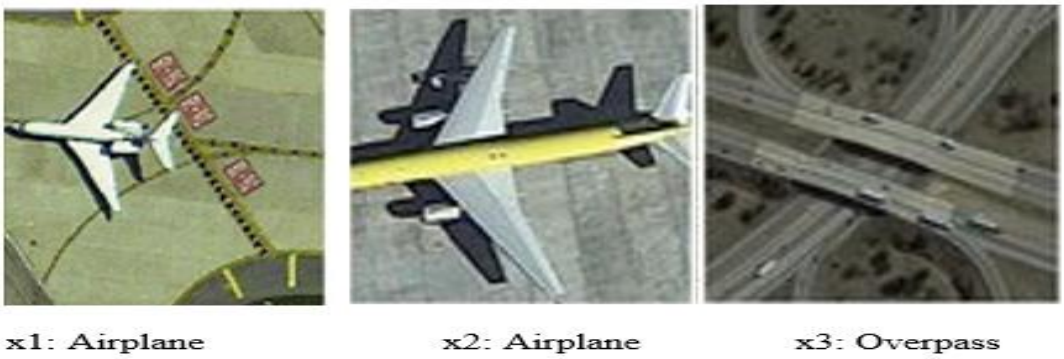

Fig7: Example of similarity function

Conclusions

Afterdoingaliteraturesurvey,weconcludethatthere isaneedofexploringfew-shot/zero-shotlearningapproachforscene classification. In this paper, we present the classificationof remote sensingimage under the N-way few-shot learningscenario.Convolutionalneuralnetworks(CNNs)haveobtained huge success in the field of scene classification. Thefutureworkincludesthesolutionforfew-shotlearningscenariosassupposedtoone-shotonly.

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