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Hyper Spectral Image Analysisinagriculture

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ABSTRACT

Satellite image classification process involves grouping the image pixel values into meaningful categories. Several satellite image classification methods and techniques are available. In existing k-means clusteringtechniqueisusedforclusteringthesatellitedata, with this method not able to cluster accurately all the classes.Inourproposed methodself-organising mapsasa clusteringtechniqueisused.Self-organizingmapslearnto cluster data based on similarity, topology, with a preference of assigning the same number of instances to each class. Self-organizing maps are used both to cluster data and to reduce the dimensionality of data. They are inspired by the sensory and motor mappings in the mammal brain, which also appear to automatically organizing information topologically. CNN Classifiers meld results from many weak learners into one high- quality ensemble model. Our proposed technique is K- Medoid clustering with CNN algorithm for classification ofsatellitedataintowater,Agriculture,Barrenland,Green Land. The proposed method of self-organising map clusteringandCNNclassifierisgivenbestresultcompared to existing ones.

INTRODUCTION

HyperspectralImaging

This project develops an advanced **hybrid machine learning system**for automated satellite and hyper spectral image classification, integrating **Self- Organizing Maps (SOM) for unsupervisedclusteringandConvolutionalNeuralNetworks(CNN) for supervised classification** to achieve superior accuracy in land cover mapping. While traditional methods like k-means struggle with complex spectral- spatial relationships in high-resolution data, our solution leveragesSOM'stopology-preservingclusteringto effectively reduce dimensionality and group similar pixels in both multispectral and hyperspectral imagery. The clustered output is then processed by aCNN classifier with subspace discriminantensembles,enablingrobustfeatureextractionand preciseclassificationoflandcovertypes—Water,Agricultural Land, Barren Land, and Green Land—while addressing the "curse of dimensionality" inherent in hyper spectral data.

Akeyinnovationistheextensionofourframework to**hyperspectral image analysis**, where we optimize band selectionandfeatureextractiontohandlehundredsofspectral channels efficiently. The system employs**random subspace ensembles**to improve generalization across diverse spectral signatures and reduce computational overhead. Rigorous evaluation using metrics like **Overall Accuracy, Kappa Coefficient, and Spectral Angle Mapper (SAM)**validates performanceonbenchmarkdatasets(Landsat,Sentinel-2,and AVIRIS hyper spectral data). Designed for real-world scalability,thissolutionsupportscriticalapplicationsin**precision agriculture (crop health monitoring), mineral exploration, and environmental hazard detection**. By unifyingSOM'sspectraldimensionalityreductionwithCNN's spatial feature learning, this project advances hyper spectral andmultispectralimageanalysis,enablingmoreaccurateand efficient Geo spatial decision-making.

The termdigital image refers to processing of a two dimensional picture by a digital computer. In a broader context, it implies digital processing of any two dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayedonahighresolutiontelevisionmonitor.Fordisplay, the image is stored in a rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display.

An image processor does the functions of image acquisition, storage, pre-processing, segmentation, representation, recognition and interpretation and finally displays or records the resulting image. The following blockdiagramgivesthefundamentalsequenceinvolvedin an image processing system.

the first step in the process is image acquisition by an imaging sensor in conjunction with a digitizer to digitize the image. The next step is the preprocessing step where the image is improved being fed as an input to the other processes. Preprocessing typically deals with enhancing, removing noise, isolating regions, etc. Segmentation partitionsanimageintoitsconstituentpartsorobjects.The output of segmentation is usually raw pixel data, which consists of either the boundary of the region or the pixels in the region themselves. Representation is the process of transforming the raw pixel data into a form useful for subsequent processing bythe computer. Description deals withextractingfeaturesthatarebasicindifferentiatingone class of objects from another. Recognition assigns a label to an object based on the information provided by its descriptors. Interpretation involves assigning meaning to an ensemble of recognized objects.

The knowledge base guides the operation of each processing module and also controls the interaction betweenthemodules.Notallmodulesneedbenecessarily present for a specific function. The composition of the image processing system depends on its application. The frame rate of the image processor is normally around 25 frames per second.

Digital image processing refers processing of the image in digital form. Modern cameras may directly take the image in digital form but generally images are originated in optical form. They are captured by video cameras and digitalized.The digitalization process includes sampling, quantization. Then these images are processed by the five fundamental processes, at least any one of them, not necessarily all of them.

Imageenhancementoperationsimprovethequalitiesofan image like improving the image's contrast and brightness characteristics, reducing its noise content, or sharpen the details.Thisjustenhancesthe imageandrevealsthesame informationinmoreunderstandableimage.Itdoesnotadd any information to it.

Imagerestorationlikeenhancementimprovesthequalities ofimagebutalltheoperationsaremainlybasedonknown, measured, or degradations of the original image. Image restorationsareusedtorestoreimageswithproblemssuch as geometric distortion, improper focus, repetitive noise, and camera motion. It is used to correct images

Image analysis operations producenumerical or graphical information based on characteristics of the original image. They break into objects and then classify them. They depend on the image statistics. Common operations are extraction and description of scene and image features, automated measurements, and object classification.Imageanalyzearemainlyusedinmachine visionapplications.

Image compression and decompression reduce the data content necessary to describe the image. Most of the images contain lot of redundant information, compression removes all the redundancies. Because of the compression the size is reduced, so efficiently stored or transported. The compressed image is decompressed when displayed. Lossless compression preserves the exact data in the original image, but Lossy compression does not represent the original image but provide excellent compression.

LITERATURE SURVEY

"“An Effective Feature Selection Method for Hyperspectral Image Classification Based on Genetic Algorithm and Support Vector Machine Authors: Shijin Li, Hao Wu, Dingsheng Wan, Jiali Zhu, Year: ,2011,Journal: Knowledge- DOI: 10.1016/j.knosys.2010.07.003”

Withthedevelopmentandpopularizationoftheremote-sensing imaging technology, there are more and more applications of hyperspectralimageclassificationtasks,suchastargetdetection and land cover investigation. It is a very challenging issue of urgentimportancetoselectaminimalandeffectivesubsetfrom those mass of bands. This paper proposed a hybrid feature selectionstrategybasedongeneticalgorithmandsupportvector machine(GA–SVM),whichformedawrappertosearchforthe best combination of bands with higher classification accuracy

“A Change Detection Model Based on Neighborhood Correlation Image Analysis and Decision Tree Classification, Authors: Jungho Im John R. JensenYear: 2005”

elementarypieceofourpriorknowledgeaboutimagesofthe physicalworldisthattheyarespatiallysmooth,inthesensethat neighboringpixels are more likelyto belongto the same object (class) than to different ones. The smoothness assumption becomes more important as sensor resolutions keep increasing, bothbecausetheradiometricvariabilitywithinclassesincreases andbecauseremotesensingisemployedinmoreheterogeneous areas (e.g., cities), where shadow and shading effects, a multitude of materials, etc., degrade the measurementdata, and prior knowledge plays a greater role.

“An Overview and Comparison of Smooth Labeling Methods for Land-Cover Classification, Author: Konrad Schindler, Year: 2012”

Vagueness in the boundaries of land cover classes is one of the important problems in the image classification.Fuzzyc means (FCM)isatraditionalclusteringalgorithmthathasbeenwidely used in the satellite image classification. However, this algorithmhasthedrawbackoffallingintoalocalminimumand it needs much time to accomplish the classification for a large data set. In order to overcome these drawbacks, a New Fuzzy Cluster Centroid (NFCC) for unsupervised classification algorithmisproposedtoimprovethetraditionalFCMandfuzzy weightedcmeans(FWCM)algorithm.Inthisworka,new objective function is formulated by adding the new term along with the distance between the pixels and cluster centers in the spectral domain.

“Classification of Satellite Images Using New Fuzzy Cluster Centroid for Unsupervised Classification Algorithm, Authors: C. Heltingenitha , Dr. K. Vani, Year: 2014”

In this paper, we present a new methodology for clustering hyperspectral images. It aims at simultaneously solving the following three different issues:1)estimationoftheclassstatisticalparameters;2) detection of the best discriminative bands without requiringtheapriorIsettingoftheirnumberbytheuser; and 3) estimation of the number of data classes characterizing the considered image. It is formulated within a multi-objective particle swarm optimization (MOPSO) framework and is guided by three different optimization criteria, which are the log-likelihood function, the Bhattacharyya statistical distance between classes, and the minimum description length (MDL).

CNNare most commonly described as performing the task of searching through a hypothesis space to find a suitablehypothesisthatwillmakegoodpredictionswith a particular problem. Even if the hypothesis space contains hypotheses that are very well-suited for a particularproblem,itmaybeverydifficulttofindagood one.Evaluating the prediction of an ensemble typically requiresmorecomputationthanevaluatingtheprediction of a single model, so ensembles may be thought of as a way to compensate for poor learning algorithms by performing a lot of extra computation. Fast algorithms such as decision trees are commonly used in ensemble methods (for example Random Forest), although slower algorithmscanbenefitfromensembletechniquesaswell.

OBJECTIVEOFTHEPROJECT

The primary objective of this project is to develop an advanced and automated system for satellite image classification by integrating**Self-Organizing Maps (SOM)forunsupervisedclustering**and**Convolutional NeuralNetworks(CNN)forsupervisedclassification**, with the goal of significantly improving accuracy and efficiencycomparedtotraditionalmethodslikek-means . The proposed hybrid SOM-CNN approach aims to accurately classify high-resolution satellite images into four key land cover categories—**Water, Agricultural Land, Barren Land, and Green Land**—and CNN's deep learning capabilities for precise feature extraction andclassification.Theprojectalsofocusesonoptimizing computational performance through**random subspace ensembles**inCNNinsatellitedata.Performancewillbe rigorouslyevaluatedusingstandardmetricssuchas**OverallAccuracy(OA),KappaCoefficient,and per-classPrecision.**

NEEDOFTHEPROJECT

In today's world, the growing demands of urbanization, environmentalsustainability,andfoodsecurityhavemadeit essential to monitor and manage Earth's resources effectively.Satelliteimageryservesasapowerfultoolinthis regard,providingvastanddetailedvisualdata oflandcover across the globe.when using traditional classification methods like k-means.This project introduces a more intelligent and efficient approach to satellite image classificationbyintegrating **Self-OrganizingMaps(SOM)** forclusteringand**ConvolutionalNeuralNetworks(CNN)** forclassification.Thishybridmethodenhancestheprecision oflandcovercategorizationinto meaningfulclassessuchas water bodies, agricultural fields, barren lands, and green vegetation.

PROBLEMSTATEMENT

Satellite image classification is a critical task in remote sensing, with applications ranging from land-use mapping and agricultural monitoring to disaster management and environmental protection. However, conventional classification methods suchas k-means clusteringand basic supervisedalgorithmsoftenfailtoachievehighaccuracydue to their inability to capture complex spatial patterns and nonlinear relationships in high-dimensional image data . Toaddressthesechallenges,thereisaneedforanadvanced classificationsystemthatcanlearntopologicalrelationships andextractmeaningfulpatternsfromsatelliteimagery.This project proposes a hybrid approach combining **Self- Organizing Maps (SOM)** for unsupervised clustering and **Convolutional Neural Networks (CNN)** for robust classification

ARCHITECTUREDIAGRAM

Self-organizing maps learn to cluster data based on similarity,topology,withapreferenceofassigningthesame number ofinstancesto eachclass. Self-organizing mapsare usedbothtoclusterdataandtoreducethedimensionalityof data. They are inspired by the sensory and motor mappings in CNN algorithm, which also appear to automatically organizing information topologically. CNN is a classificationmethod.Theproposedsystempresentsanovel approachfor satellite image classificationbycombiningthe strengths of **Self-Organizing Maps (SOM)** for clustering and **Convolutional Neural Networks (CNN)** for classification. This hybrid model is designed to address the limitationsoftraditionalclusteringtechniqueslikek-means, which often struggle with non-linear data, high dimensionality, and poor accuracy in classifying complex land cover types.

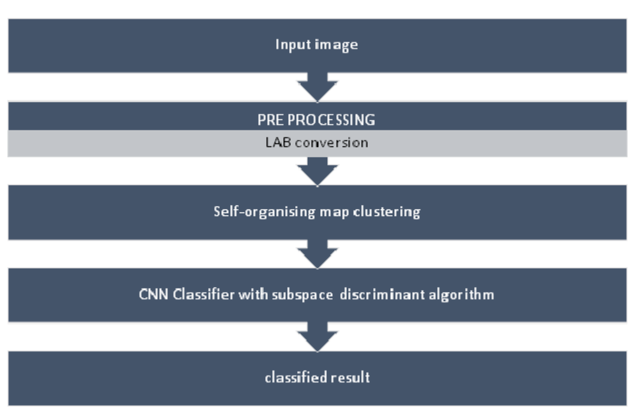

Fig1.1ARCHITECTUREOFPROPOSED SYSTEM

METHODOLOGY

The Input Images is land set satellite Image. This image contain green, barren land, crop and water. So we are going to classify 4 classes in that image. The input satellite image is converted to LAB colour space and reshapetheimagedataforapplyingself-organising map clustering technique.

Self-organizing maps learn to cluster data based on similarity, topology, with a preference of assigning the same number of instances to each class.Self-organizing maps are used both to cluster data and to reduce the dimensionalityof data. They are inspired bythe sensory and motor mappings in the mammal brain, which also appear to automatically organizing information topologically. Discriminant analysis is a classification method. It assumes that different classes generate data based on different Gaussian distributions. Use random subspaceensembles(Subspace)toimprovetheaccuracy ofdiscriminantanalysis. Subspace ensemblesalso have theadvantageofusinglessmemorythanensembleswith allpredictors,andcanhandle missingvalues .Thebasic random subspace algorithm uses these parameters. *m* is the number of dimensions (variables) to sample in each learner. Set *m* using the N Pred To Sample name-value pair.*d* is the number of dimensions in the data, which is thenumberofcolumns(predictors)inthedatamatrix X. *n* is the number of learners in the ensemble. Set *n* using the N Learn input.The basicrandomsubspace algorithm performs the following steps:

1. Choosewithoutreplacementarandomsetof*m*predictorsfro mthe*d*possiblevalues.
2. Trainaweaklearnerusingjustthe*m*chosenpredictors.
3. Repeatsteps1and2untilthereare *n*weaklearners.
4. Predictbytakinganaverageofthescoreprediction oftheweaklearnersandclassifythecategorywiththe oftheweaklearnersandclassifythecategorywiththe highest average score.

IMPLEMENTATION

The proposed satellite image classification system is implementedusingMATLAB2017a,utilizingseveralbuilt-in toolboxes including the Neural Network Toolbox, Deep LearningToolbox,and ImageProcessingToolbox.Thesetools support both unsupervised clustering using Self-Organizing Maps (SOM) and supervised classification using Convolutional Neural Networks (CNN). The input dataset comprises original high-resolution satellite images of the Kakinada region, stored in TIFF format, capturing multiple land cover types suchas water, greenvegetation, barren land, and agricultural areas. The implementation begins with the acquisition and preprocessing of the satellite images. Each imageisresizedtoastandardresolutiontoensureconsistency across the dataset. The color space of the image is converted fromRGB to LAB, whichprovidesbetter separationbetween luminance and chromatic components. Once the image is prepared, a Self-Organizing Map is used for unsupervised clustering. The SOM is initialized witha 2×2 grid tosegment theimageintofourmainlandcoverclasses.TheSOMtraining process uses competitive learning, where the neuron whose weights areclosest to theinput.Theclustered image fromthe SOM serves as a pseudo-labeled dataset to train a Convolutional Neural Network (CNN). The original image is resizedappropriatelyandusedasinput tothe CNN, while the SOM outputactsasthe ground truth. After training, the CNN is used to classify each pixel in the satellite image. The final result is a segmented image where each region is labeled as one of the four predefined land types. The output is visually interpretable, with clear boundaries between classes and accurate representation of real-world terrain.

EXISTINGSYSTEM

Thisprojectsolvesthe problemofunsupervised land-cover classification of remotely sensed multispectral satellite images from the perspective of cluster ensembles and self- learning. A cluster-ensemble- based method is proposed herefortheinitializationoftheunsupervisediterativeSVM algorithmwhicheventuallyproducesabetterapproximation of the cluster parameters considering a certain statistical model is followed to fit the data. A novel method for generatingaconsistentlabellingschemeforeachclustering of the consensus is introduced for cluster ensembles. The EM algorithm approximates cluster parameters assuming that clusters are Gaussian distributed. The final classification is obtained by a maximum likelihood (ML) classifiertrainedontheupdatedparametersproducedbythe SVMalgorithm.Theproposedmodelcomparewithexisting algorithm SVM, k-means, k-NN. The clustering performance of the proposed method on a medium resolutionandaveryhighspatialresolutionimageandhigh accuracy.

Cluster Ensemble Initialization: Multiple clustering results(e.g.,fromk-means,DBSCAN,etc.)arecombinedto form a consensus labeling.

Self-LearningSVM: ThisSVMistrained iterativelyusing pseudo-labels derived from cluster ensembles.

EM Algorithm (Expectation Maximization): Used to refine the parameters of the Gaussian distributions assumed for each class.**Maximum Likelihood Classifier (MLC):** Final classification is performed using MLC based on the refined parameters. **Dataset:** *Landsat 8 Multispectral SatelliteImage***BandsUsed:**Red,Green,Blue,NearInfrared (NIR),ShortwaveInfrared(SWIR)**Region:**Urbanandsemi- urban areas with diverse land cover types (e.g., vegetation, water, built-up, barren land)

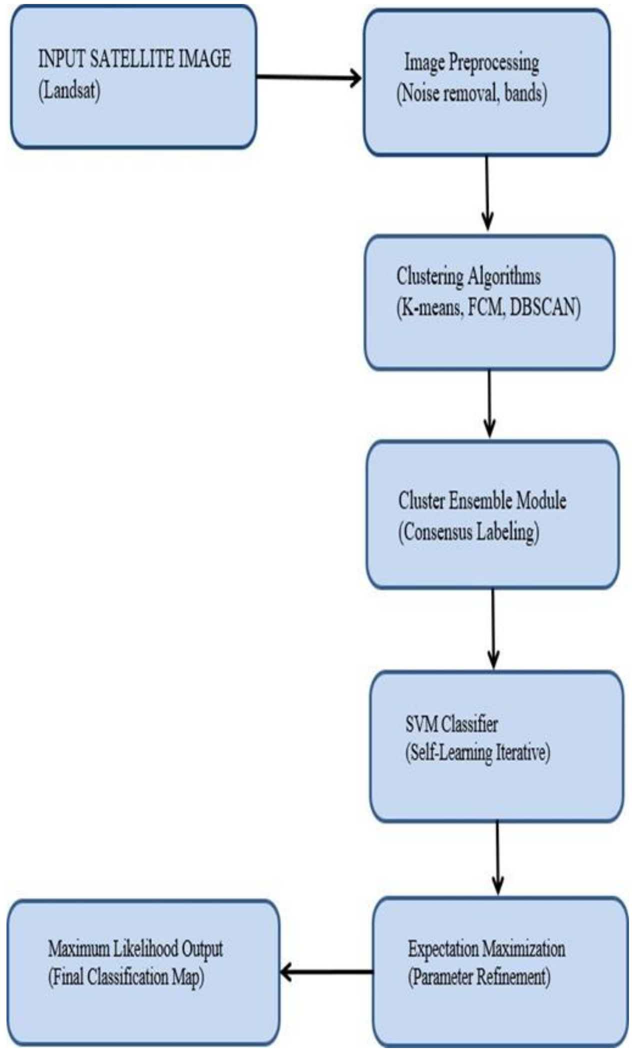

FIG1.4EXISTINGARCHITECTURE

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