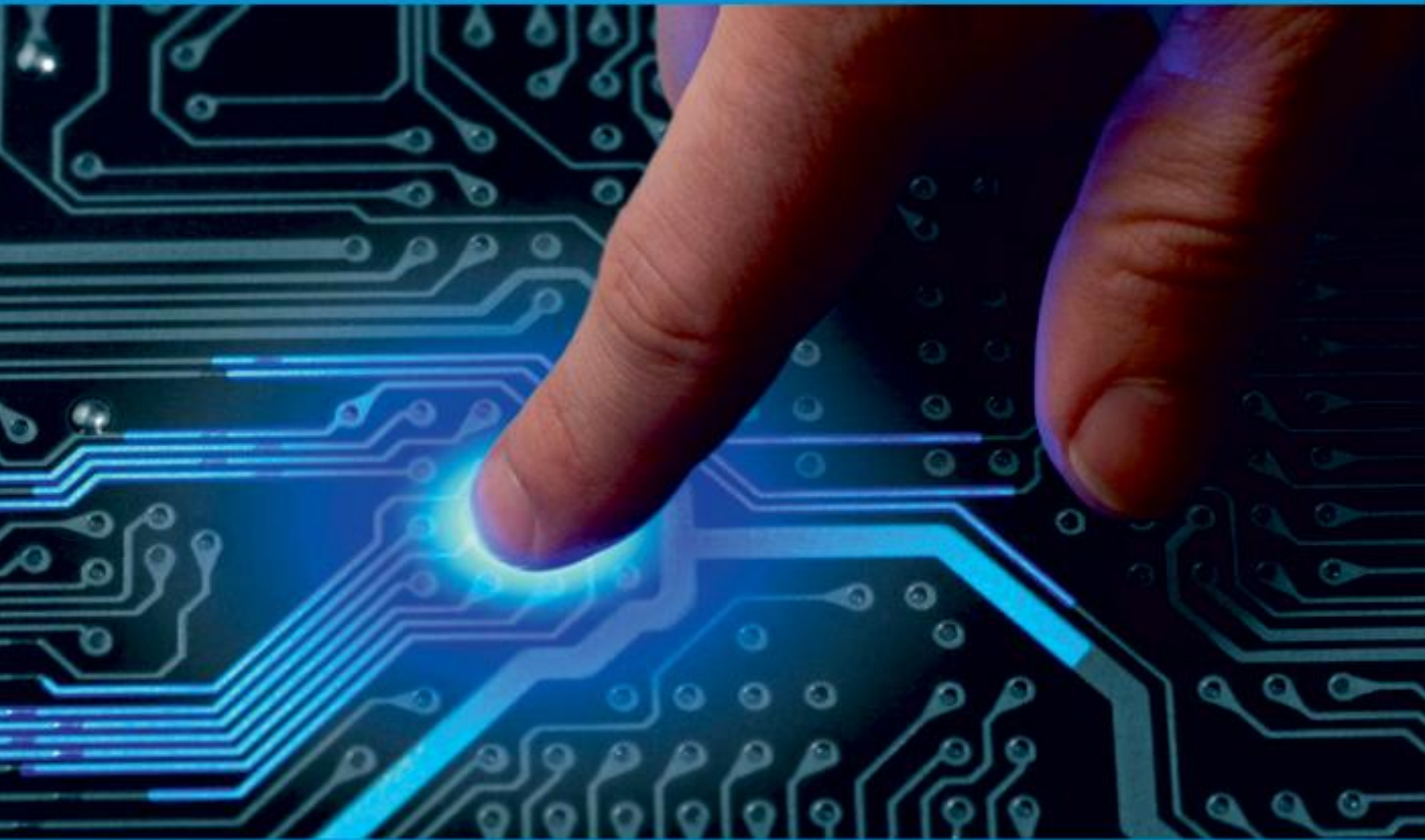
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 11, Issue 5, May 2023

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 5, May 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1105340 |

LULC Scene Classification Algorithm

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ABSTRACT: Numerous deep learning(DL) algorithms have been developed for imageclassification in response to the large amounts of satellite data (SD) that are now available. DL have been shown to perform better in recent studies for a range of tasks, from object identification to semantic labelling, but their adaptation accuracy in scenes classification (SC), such as those fromSD for land use and land cover (LCLU), has been low.This is explained by the dearth of larger annotated training datasets as well as the appearance of new problems such intra-class to class variation, swift label changes among surveys, and the creation of new classes in specific locations. A sizable volume and range of training data are required for DL to build the complex network architecture required to achieve the best classification accuracy. The scale of the considered networks has been constrained by the restricted number of annotated training datasets for remote sensed(RS) classification, resulting in low satellite image classification accuracy.By integrating the datasets from EuroSat and UC-Merced (UCM), this research builds larger training set of twenty nine thousands (29000) scenes, with twenty nine (29) classes of LULC for an adaptive DLSD classification. In order to conduct superior large-scale scene classification, we increased the number of considereddeep networks and hyperparameters.Transfer learning (TL) was used to test the adaptability of the novel model on new locations and was able to expand a collection of LCLU new classes to datasets with limited number of LULC class description. On various SD, classification accuracy of 99.7% were achieved using the algorithm. The established classification model opens up a wide range of satellite technology options. We talk about the potential applications of this approach for LULC categorization in disaster management, environmental monitoring, and climate change.

KEYWORDS: RS, SD, Adaptive Algorithm, LULC, Scene Classification,

I. INTRODUCTION

The rapid development of contemporary RSsystems has made a significant collection of information on earth's surface science. This has made a variety of RS applications possible[1]–[3]. We can be grateful that the era of open and increased accessibility to SD has arrived. [4]–[7],[8]. Numerous initiatives, such the Copernicus mission of the ESA and the Landsat project of NASA, are making significant initiatives to provide data openly to support modernization and innovation in both private and public sectors. [9]. Applications in the disciplines of agriculture, disaster recovery, climate science, urban development, and environmental monitoring can be accomplished with availability of such datasets. [9],[10],[11]. However, fully utilisation of the data in these domains requires rigorous processing of the satellite data and converting it into structured interpretations[9][12]. LULC classification is an examples of such basic semantics[2][9]. Satellite image semantic annotation, which is a task of assigning one or several predefined semantic concepts to an image according to its content, plays an important role in the aforementioned applications and has received increasing interests[2].In order to automatically offer labels indicating the characterised physical land type and usage, LULC classification is used for example, forestry, water, settlements, industrial, and many more classes [9][13].

Adaptation by many algorithms for RS data classification is still a big challenge. Given that it serves as the foundation for many other computer vision issues, image classification is thought to be the primary task across all[14]. It is important to note that we refer to the classification of remote sensing (RS) images at the pixel, object, and scene levels collectively as "remote sensing image classification"[15][16]. Approaches to pixel categorization are plagued by two fundamental issues. The significant computational expense that results from source images single pixel classification and, as discussed by Marinai[17], the training of pixel classification algorithms can be problematic in the frontier of regions where near equivalent inputs to the classifier can correspond to different classes. Detecting objects is the goal of object-level image classification. [17][16]. Pixels are divided into vector space by the edge detection, with each having its own spectral properties and indices of the median values, minimum and maximum values, variance, and texture. From this process, image objects are formed. [18]. There are several ways to classify objects. For example, geophysical objects, having real life context, are formed by an iteration of region growth, (see Fig 2b). Classifying RS images at the object level have dominated satellite image analysis in the last twenty years. [16][18]. But because As SD become increasingly more sophisticated, they potentially contain vast number of distinct sectors .The methods at the pixel and object levels might not always be sufficient to accurately classify them. SC is crucial because it facilitates the understanding and interpretation of global contents of RS data.SCtargets individual RS image square (eg., 64x64x3) into a relevant class,. Scene, in this sense, entails a visual patch which was clipped from satellite image, it comprises discrete spatial meaning. [19][16].

Authors, [9][20][21] suggest that, accessibility of large-quality training samples with sufficient selection of classes is essential for supervised ML image classification algorithms. Taking the present progress of deep convolutional neural networks (DCNNs) specifically [22] [12], to train deeper network, significant big amounts of training samples must be accessible[9][12]. Recently, DL have surpassed all other machine learning models in a variety of fields.Unfortunately, obtaining a sizable labelled dataset for DL has proven challenging.The absence of comprehensive annotated data, which is typically available for other visual modalities, is a serious issue in the RS domain due to our extensive collection of SD[23][9][12][20]. Under this paper, LULC classification using the DCNN framework is investigated using SD. In order to solve lack of huge labelled RS scene datasets, we merged two techniques with DCNN: Initially, combined the existing training datasets from EuroSat and UCM to come up withunusual larger training setwith 29 unique LULC classes for SC.Additionally, increased number of network, as well as hyperparameters and optimization for SC.This research will make use of publicly available EuroSAT consisting 27000 annotated images with ten unique classes[9] and 2100 labelled scenes of UCMerced collection, divided into twenty one separate classes. Dataset will be pre-processed to match in size and dimension using data augmentation techniques.

II. LITERATURE REVIEW

a) Traditional M L Methods for LULCClassification

1) Random Forest (RF) Based Classification

RF classifier is constructed from multiple independent decision trees. Every single of those trees generates new subclass for a specific experiment. The result is determined by class-label selected more by bulk of such trees. The class label chosen by the majority of the trees determines the final outcome. The result is extremely accurate and noise-resistant because there is no such association among those independent models. [24]. Within classifiers, RF became best solutions for change detection modelling, as it have greater efficacy, reliability, limited calculation effort, and need for just few features. While DL and DTL approaches recently emerged as efficient computational strategy in ML, both techniques are time- and resource-intensive and have a limited ability to do sophisticated calculations on cloud platforms[25].

2) Support Vector Machine (SVM)

A hyperplane is developed by support vector classifier to split classes. When extra measurements were required to split the data evenly, they were incorporated into those parameters. Based on categorisation circumstance, many parameters, such as radial functions, may well be applied. The SVC method has some variables that may be adjusted for enhancing the result. Sk-learn module provides two approaches for performing multi class classification using SVMs: one-versus-one and one-versus-many classifiers. The first one separates is developed for every NC2 possibility of target class. Typically, one-versus-many classifiers are favoured since they require less effort. Once a test instance has been collected, the classifier that successfully classifies the instance positively and has the highest confidence value is selected..[26], [27][24].

3) Logistic Regression Classifier(LRC)

LRC technique solve classification relativelyin simple way. LRCclassifies images by using activation function such as sigmoid. LRC has many times that includes, binary LR, mostly binary-class issues. OVRtype is used classify multiclass datasets. While using LRC, result threshold must be given. It will be classed as one class if the output of the activation function is less than the threshold value; otherwise, it will be classified as the other class[24].

b) Deep Learning algorithms for Scene Classification

In this subsection, we give a quick overview of some important DL concepts, particularly CNN, which should be useful in understanding the methodology used in this study. CNN, has number of networks, and other features such as hyper parameters, regularization, optimization approaches, and loss functions that makes its uniqueness and most adopted classification model.Due to its superior performance compared to that of conventional learning algorithms, DL has recently emerged as the big data analysis trend that is expanding the fastest[23]. As per biology, this serves as the foundation for DL. Again for human mind, perception is also reflected at various levels of abstraction. Ml algorithms

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 5, May 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1105340 |

are ANNs that have more and over two layers. As its deep relative, DNN utilize features that were entirely taught from data. They need not, nonetheless, require hand-crafted features, which are typically created using domain context expertise. [28]. DL scene classifiers use image inputs and outputs of numeric attributes for a given class. DL classifier takes input features, use backpropagation processes, to learn and classify. Best scene DL classifier models, as of today.

1.**CNN**

Conventional NNs have difficulty scaling to the photographs because several properties are required to be learned. A number of trainable filters make up the Convolution Layer, which is the main component of CNN.The filter has fixed measurements but occupies the entire depth of the input matrix.This contextual characteristics is also referred to as the kernel size the input picture is convolved with each filter (which represents shared parameters), producing atwo-dimensional feature map. When the filter correlates well with a section of the input image, the response in the relevant feature map location is strong. The number of filters in each layer, stride, and padding are the additional hyper parameters in CNN. Whenever we move the filter to convolve with theinput image, the stride is the number of pixels that must hop. The output volume decreases as the strideheight increases. In order to preserve the size of the output volume so that its width and height are identical to that of the input volume, padding is the practice of padding the input volume with zeros at its boundaries.

c) LUCU Dataset challenges

Yang et al. introduced the widely used and well-researched UCMerced (UCM) land use dataset[29],[30], a RS image classification dataset[9][2], [12], [31], [32][33]. The train set contains twenty one categories. Each photograph has a size of 30 pixel and there are hundred pictures per class. The underpinning images RGB imagery having pixel size pixels 256. Images were all obtained from the USGS NMUAI collection.A sample containing 100 images for every class is unfortunately rather tiny.

Various efforts have manually created unique datasets using commercial Google Earth cropped pictures in an effort to improve the dataset situation [34][35],[36], [37] just like benchmark datasets by PatternNet [38] and NWPU-RESISC45 [7]. Imagery with such a 30 cmx30 cm pixel size are used to create the data. Even though labeling a sample requires a lot of effort, these samples had only just few 100 photos per category. The aerial image dataset (AID) is one of the biggest datasets[34]. Collection has 30 classes with 200–400 satellite images per class. The images of 600 x 600 pixels were also taken from Google Earth image.

Penatti et al. conducted research to classify satellite imagery [3], [9], [23].To categorize coffee plants, he employed one thousand four hundred SD information with a spatial resolution of 10 m/pixel.R,G and near-infrared bands make up the images..

Basu et al.[10] , presented the SAT-6 trainset that uses airborne photography. SDwas taken from pictures with a 1 m/pixel spatial resolution. The NAIP images were used to produce the image patches. The collection has six classes. Each of the proposed squares measures 28 pixels and has a RGB, and near-infrared Channels. The NWPU training set is among the most challenging. Pictures of RS, photogrammetry, GIS, and other sources are used to depict well over hundred locations on Earth. Since information were gathered from diverse perspectives, in varied lighting conditions, and over numerous periods, it has fair amount of similarity within the separate classes.There are 45 different patch classes inside the set, and each one is 256 pixels in size. There are seven hundred photographs per class, for a total of thirty one thousand five hundred. It has a wide range of spatial resolution: 0.2–30 m [31].

1) Review of LULC Methods Addressing the Data Sparsity and Scalability

The conventional and DL techniques of LULC classification require labelled training sets to be considerably comparable spatially, to the picture in order to function.SD from many LULC show drastically diverse spatial structures, difficult to extract features within a single dataset, this is difficult.To solve these challenges, which were specific to SC, algorithms were developed, either from the satellite image classification field orfrom ML or computer science domains.In this research we provided a general review of these techniques and challenges in RS classification. Sections two to four briefly examines these areas.

2) Poorly/Semi- Supervision Datasets

Techniques that are poorly supervised include the algorithms, treats training sets as noisy inputs. These inconsistent and incorrect inputs”[39] could be divided into a variety of instances: Firstly, train samples that cannot adequately represent the spread of testing images are insufficient. Furthermore, erroneous; for instance, scene versus pixel patches have unique resolutions. Training inputs and their annotations mismatch the testing outputs. The final erroneous factor is that inputs and annotations are flawed and contain errors. There is only one minor difference between semi-supervision and weak supervision: semi-supervision anticipates that a sizable share of raw datasets will yield negligible sample/feature densities. In the SC situation of "unequal scenes," poor/semi-supervision are usually combined. These little

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

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inconsistencies are repeatedlyunheededfor because the unlabelled data used in SC systems is so large. Such methods often focus on the training procedures themselves, including data augmentation or developing regularisations to conventional and DL architectures, to avoid overfitting[15].

3) Transfer Learning and Adaptation

Using knowledge learning from unique DL activityto a different environment without further learning is referred as TL. Using the knowledge gained from object classification job, for example, to complete the facial recognition problem[40]. This notion in SC, refers to use dataset for training an algorithm, now use the learned algorithm to classify dataset that has is unlabelled or with fewer classes. It is crucial whenever the data sources come from different geographical areas or are collected from different instruments and systems[40]. Domain adaptation (DA) techniques must be applied in this case since the characteristic spans acquired from either the input were diverse, making it important to lessen the differences with in features among data sets. Target domains are those containing few or no labels, whereas source domains are those with labelled data.DA and algorithm reconfiguration represent the only two fundamental types of TL concepts employed with SC.The differences on inputs and outputs feature densities is referred as domain-gaps. Mostly are soul explanation of generalisation by ML algorithms.Figure1. shows a straightforward scenario that depicts the distribution of radiometric measurements across various train-sets: [41].

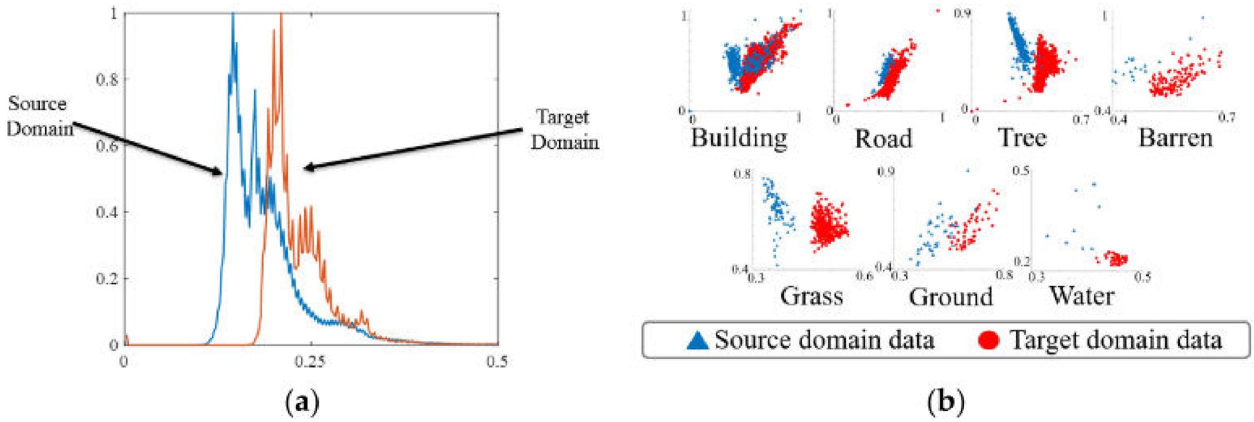

Figure 1: domain breaksamongstinput and output: (a) Poordispersal of radiometric metrics; (b) mismatches amongst classes.

4) Model Fine Tuning (MFT)

One distinct type technique known as MFT was made famous alongside deep learning techniques, and it aims to relearn a portion of a previously neural model (such as ImageNet[21]) with considerably smaller training data. Technically, makes use of rigorously trained algorithm to smaller not trained with less classes sets.

d) Related Work on DCNN LULC Classification Models

A form of neural network called a CNN has produced positive outcomes on satellite data problems[42], [43], [21], [44]. The most advanced SC method in computer vision and ML is CNN, which gained prominence as it became more widely used. Just on UCM training sets, Yang and colleagues examined number of classification labels and spatial extension techniques. [33].

Basu and his team examined DBNs, convolutional neural networks, and denoising autoencoders on the SAT-Six trainsets[10]. A unique design of the LC classes'datasets was also presented by Basu et al. The algorithm takes the input features, normalizes them, and feeds them to Deep Brief Networks.

Penatti and colleagues evaluated DCNNs along with basic colour classifiers on the UCM and BCS training sets. In order to supplement DCNNs for the segmentation of the UCM and BCS training sets, Castelluccio et al. thoroughly evaluated a variety of ML approaches, including BoVWs and SPARK. A fresh pretrained NN was utilized within context of DL[29], [45],[46], [30], [47]. The TL of pretrained models on scenes out of a completely other area was made successfully. Nevertheless, the pretrained networks showed RS data classifying efficient. [48]. The given work thoroughly analyzed every suggested ML techniques and came to the conclusion that on training sets under consideration, DCNNs surpassed non DL alternatives. [29], [49],[46][34].

The planned EuroSAT training set by Helber and colleagues.,[9]with images consists of thirteen spectral bands, is divided into 10 classes, and has a maximum of twenty seven thousand annotated and spatial scene. In order to generate advancements for such a distinctive datasets, plus other channels not RGB, current DL were applied. A successful SC

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 5, May 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1105340 |

accuracy of 98.57% achieved, even with the suggested creative sample. Researchers used GoogleNet and the DCNN, ResNet-50 to classify the newly created LCLU classes.Likewise, the algorithms used both a residual constituent and an inception element.

IARPA's fMoW training sets contains items and amenities that Pritt et al.[[32],] classified across sixty-three various classes using DL technique. The system is made up of a combination of CNNs as well as other Networks that blend images qualities with SD. The model's classification accuracy was 95%..

III. PROPOSED ALGORITHM

A. *Design Considerations:*

- Increase the number of labelled satellite image scenes.
- Include all scenes from different sensors platforms and LCLU environments
- Increase the name of labelled classes of LULC.
- Keep track of the previous state of the DL models.
- Consider all possible modifications on building parameters, optimizers and number of networks
- Test the Adaptation of the novel Algorithm to the new dataset.
- Evaluate the novel algorithm against state of the art algorithms.

B. *Description of the Proposed Algorithm:*

Major objective of the research was to enhance the DL SC algorithm on LULC adaption utilizing SD. To accomplish the goal, the research design techniques listed below will be utilized:
Step1: Prepare a combined big scene dataset using EuroSat and UCM datasets.
Step2: To evaluate the performance of existing CNN architectures on SC.
Step3: To develop anovel DL algorithm for SC adaptive differentLULC datasets.
Step4: To evaluate the proposed algorithm adaptation on different SD.

IV. PSEUDO CODE

Step 1: Generate a big dataset from EuroSat and UCM datasets.
Step 2: Increase number of labelled classes.
Step 3: Evaluate previous published scene classification models.
Step 4: Select the best DL model and modify to new novel model.
Step 5: Modify the novel model, by increasing number of considered networks.
Step 6: modify the novel model batch size, filter size, hyperparameters, optimizers, and activators.
Step 6: Calculate performance accuracy and loss over each epoch.
Step 7: Go to step 5.
Step 8: record best score over that of step 3
Step 9: End.

V. RESULTS AND DISCUSSIONS

a) Data Cleaning

Different patches from the two SD sources have preprocessed in terms of dimension and spectrum wavelength.The presence of label noise SD, which are often non-standard, therefore extremely mistake prone, is among main obstacles in building DL algorithms for SC. Feature extraction were applied a variety of ML techniques.Under this study, 3 distinct synthetic labeling noise types, i.e, NCAR, NAR, and NNAR—were applied to the training sets.After algorithm training, uncertain sample sets, their computing efficacy was assessed to noise-free SD. class.The spread of images within classes on novel dataset SD is shown on figure 2.

b). Evaluation of models on EuroSat and UCM dataset

Training sets, UCM and EuroSat, were utilized to assess researches on SC for LULC.The evaluation focused on SC on the RGB channels. The corpus of the research articles some of which were used evaluation of existing algorithms on SC for LULC.Criterion accuracy comparisons were made initially to every sample sat independently (view tables 1 and 2). Due to the use of smaller datasets with fewer classes, the results indicate that in both instances, the models classified relatively less accurately than our novel algorithm.

Table 1: Top EuroSat SC Accuracies

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Serial	Model	Accuracy (%)
1	µ2Net (ViT-L/16)	**98.9**
2	ResNet50	**98.65**
3	MoCo-v2 (ResNet18, fine tune)	**97.5**
4	MSmatch Multispectral	**94.4**
5	SEER (RegNet10B-Linear eval)	**92.2**
6	MoCo-v2 (ResNet18, linear eval)	**92.2**

Table 2: Top UCM SC Accuracies

Serial	Model	Accuracy (%)
1	µ2Net (ViT-L/16)	**100**
2	ResNet50	**99.61**
4	MSMatch	**98.33**

b) Novel Algorithm Performance

Running on GPU tensflow environment. The algorithm's accuracy over mere hundred iterations achieved 99.69%, while its validation accuracy was 91.41%. Comparatively speaking to earlier algorithm designs, ours performed better. Increased number of LULC classes to twenty nine on the novel datasets comprised of 29000 plus scene has proved to be recommended approach in solving DL issues in SC.

VI. Conclusion and Future Work

We developed a novel algorithm for SC with adaptive capability to be reused in scenarios where scarcity of labelled datasets or availability of limited labelled classes is common. The algorithm was able to learn and achieved 99.6 % classification accuracy on newly built datasets. City planning, agricultural production, natural incidents management, climatology, and surveillance systems are all areas where LULC is of crucial importance. The novel algorithm performed better when employed several metrics such as deep networks, hyperparameters, and optimization to carry out large-scale scene classification.

In our further studies, datasets with more named classes and coverage of other geographic elements, such as multiple wavelengths datasets and per band training will be conducted.

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| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 |

|| Volume 11, Issue 5, May 2023 ||

| DOI: 10.15680/IJIRCCE.2023.1105340 |

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