Artificial Intelligence for Land Cover and Land Use Classification in Remote Sensing: Review Study

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***Abstract*—Remote sensing imagery data presents difficulties when attempting to classify Land Cover and Land Use (LCLU). Since we are now living in the age of ”Big Data”, there is a tremendous increase in the volume of Remote Sensing (RS) measurements used for environmental protection that need interpretation. Deep Learning (DL) approaches have been developed as a current effective modeling tool to recover information from large remote sensing pictures for LCLU identification, allowing them to be used for this pressing problem. For asset preservation and nature conservation, it is crucial to classify data gathered remotely in the geologic domain. In recent years, LCLU classification using remote sensing image data has seen a rise in the use of deep learning techniques. The use of deep learning techniques, such as Convolutional Neural Networks (CNN) and recurrent neural networks, is enough for classifying remote sensing picture data. They propose to use deep CNNs to verify and assess their results using a variety of criteria. This paper presents a comparative study of the different methods used in Land Cover Land Use Classification to find out the best available method based on their accuracy.**

***Index Terms*—Land Cover and Land Use (LCLU), Artificial intelligence, machine learning, deep learning, Convolutional Neural Networks (CNN), algorithms, and classification.**

I. Introduction

Computer visions, as well as image processing, are two areas that might benefit from new methods and features made possible by Artificial Intelligence (AI). Within the context of this idea, the use of DL algorithms is expanding dramatically owing to the fact that it is reliable and requires fewer human operations. The discipline of deep learning is still very much in its infancy and has not yet reached its full potential in any way. As a result, land use categorization of remotely sensed data is going through a period of remarkable expansion, and the application of DL algorithms as approaches has been growing over the course of the last five years. In the most recent years, a great number of new difficulties and datasets have emerged in relation to the use of DL in remote sensing. A great number of CNN models make use of Earth observation data, such as satellite photography and aerial photographs. Hidden feature extraction is a stage that is included in DL. The algorithm operates to generate an accurate estimate by its own information processing by utilizing its artificial multi-layer neural network architecture, which includes a hidden layer. Applications of deep learning that use remote sensing images may be categorized as object identification, classification, as well as segmentation, respectively. The goal of the existing research domain in the field of satellite imaging known as land cover and land use or LCLU categorization is to categorize a particular RS picture with the physical cover along with information about man-made structures that are present within the image. This research place is defined as LCLU categorization. The LCLU classification has many different applications in the actual world, including the monitoring of the environment, the identification of geographical objects, the study of urbanization, and the examination of natural disasters. The coordination of information on the environment program is one example of a global effort that has greatly contributed to the promotion of the adaptability of LCLU activities. This program is financed by NASA and also The European Union (EU). The advent of Remote Sensing (RS) platforms that are capable of capturing a wide variety of resources as well as an upsurge in remote sensing data volume that now has recently been developed accessible via globally accessible delivering services platforms have facilitated access to the vast variety of high RS images and launched a new era throughout deep learning-based investigation on RS. This research had already opened the way for a new period of investigation on RS. This review paper explores common AI approaches for LCLU and compares their results to identify the most effective methods.

II. Background

The advancement of RS technology has resulted in a number of new challenges, the most significant of which is that RS photos now vary in fundamental ways from traditional photographs. This is a challenge that can’t be sidestepped in any way. In light of these considerations, the RS pictures are very distinct from the normal images because of the fact that now the RS images encapsulate more complex patterns and exhibit a different level of complexity as just a result of the consequences of internal and external deformations that occurred during the process of data collection. In other words, the RS images are now more complicated than natural images. As a result of this, LCLU classification presents a number of challenges as a result of the fundamental properties of RS images, like the effects of the atmosphere and topography, the earth’s curvature, temporary and time-based modifications, random bad pixels, problems with line starts and stops, line or section striping, as well as drop-outs throughout data acquisition. In recent years, several approaches to the LCLU categorization of satellite pictures have been up as potential solutions. When taking into account the use of the characteristics from various perspectives, these approaches separated into three primary groups and then became distinguishable: human-engineering-based approaches, unsupervised feature learning-based techniques, and deep feature learning-based techniques. The prior work on LCLU classification was mostly focused on conventional techniques that make use of hand-crafted features such as scale-invariant simple modification and GIST. These methods have now been superseded by more modern approaches. These techniques put an emphasis on the visual assessment provided by the visual analyzers and include only low-level characteristics; as a result, the description of the picture is severely constrained. On the other side, unsupervised learning approaches like k-means clustering as well as auto-encoders are used in order to automatically characterize the picture characteristics in the absence of any label information. As a consequence of this, it seemed as if these procedures were more practical than those that were dependent on visual interpretation because of their capacity to extract the characteristics straight from the picture. Nevertheless, current methods of unsupervised learning are unable to get their full value from picture class characteristics.

IV. Remote sensing

RS refers to both the art and also the science of gathering information about such an item or phenomenon via the use of sophisticated sensing technology without having to make direct physical touch with the target. The RS technologies generate a great number of RS photos each and every day, and these images might be derived from the atmosphere of the planet or outer space and collected [19]. Sensing technologies comprise remote sensors that capture a significant number of RS pictures from the earth's surroundings in which they are placed under observation. It is possible that development cannot occur without careful management, control, and planning of the land. It is possible that providing help for the jobs using LCLU classification methods that are machine-aided would be preferable. As a result, the LCLU classification issue has recently emerged as the primary focus of study in the RS pictures domain. The LCLU classification challenge in RS pictures might thus be addressed by presenting the deep learning (DL) method to the problems. DL is a powerful and relatively new method of machine learning (ML) that offers significant improvement for RS pictures [10].

V. Machine learning algorithm

In the field of machine learning, predicted models are constructed with the assistance of different classifiers. These algorithms divide incoming data samples into several categories based on the characteristics with which they are characterized. The characteristics that are employed to define data samples are directly related to the level of accuracy achieved by these classification techniques. There are certain qualities that are more beneficial than others for identifying between different data samples. Some of the characteristics are either unnecessary or irrelevant, which has a detrimental impact on the prediction model's performance as well as its level of complexity. These strategies aim to select the best possible set of features to improve classification accuracy while simultaneously reducing the number of computations needed to construct and train predictive models. Techniques for selecting features may typically be divided into three groups, which are as follows:

Filter-Based Methods: Before developing the machine learning technique, such feature selection approaches utilize some function to rank the collection of features, and then they filter away irrelevant attributes with rank values that are lower than a particular threshold. The effectiveness of these methods is directly proportional to the degree of the ranking function that is applied to the characteristics.

Wrapper-Based Methods: In this subcategory, irrelevant characteristics are not omitted from consideration before the model is constructed. Instead, a classifier is employed to eliminate unnecessary characteristics from the data. It is possible to train and validate the model using a variety of different subsets of features. After doing so, the feature set that yields the highest classification accuracy is chosen as the optimum subset of features. These approaches may have a very computational complexity, which increases the likelihood that they will provide a solution that is less than ideal.

Embedded Methods: These strategies use a combination of different approaches in order to choose the most useful subset of characteristics. In contrast to wrapper-based approaches, it doesn't really entail repeated classification with varying feature selection methods. This is done to reduce the high computing cost of wrapper-based methods. These approaches, in contrast to filter-based approaches, do not use a system in order to rank the characteristics. Instead, the rankings of features might be derived from the results of the classifier, like the weight of input data in neural network models.

VI. Use of Machine Learning in Classification Systems

In the northern regions of the United States during the course of the last two decades, significant areas of grassland have already been changed to accommodate a variety of various land uses. The Great Plains The majority of LCLU analyses carried out in this area have relied heavily on Cropland Data Layer from the Agriculture Department, which might have some inconsistencies. In this article, we provide a methodology for mapping land cover that makes use of multi-temporal Remote Sensing data from Landsat as well as MODIS. [1] The fitted model's phonological measures, as well as the metrics generated from them, In order to investigate how the RFC is affected by factors like sample size and design, we carried out classifications using a variety of possible sample selection processes. According to the findings our suggested technique was successful in precisely mapping the primary crops found in the research region, but it demonstrated only limited accuracy when mapping non-vegetated land coverings. Estimated land cover areas derived from various models may vary greatly, despite the fact that all RFC models have a high level of accuracy; this suggests the need of doing a thorough investigation into model stability in just about any prospective land cover supervised categorization [1]

Within the scope of this study [2], we tackle the issue of land use and land cover categorization using Sentinel-2 satellite pictures. Here is a rundown of the most important contributions: Here, on the basis of our original dataset, on photos taken by the Sentinel-2 spacecraft spanning thirteen distinct spectral bands and consisting of ten different classes, with just a total of 27,000 bands that have been designated images. On this recently discovered dataset with its many spectral bands, we conduct an analysis using the most advanced deep convolutional neural networks (CNNs).

A novel data source that may be used for the categorization of land cover is provided by multi-spectral Light Detection and Ranging (Li-DAR). The spectrum of spatial geometry data collected by this kind of Li-DAR stands out for being comprehensive and precise. Due to its comparatively high feature learning or maybe even feature expression capabilities, the convolutional neural networks or the CNN must have spawned a succession of breakthroughs in image analysis, object identification, and picture text classification during the last several decades. This is in comparison to machine learning approaches, which have not made as many strides in these areas in recent years. Conventional CNN models, on the other hand, have a number of drawbacks, including a large number of layers, which results in a greater computational cost.

VII. Deep Learning

Classification systems for land cover and land use (LCLU) that are powered by deep learning are becoming an increasingly important goal for the remote sensing community. Images obtained by remote sensing provide a wealth of information about the natural world, all of which must be processed. Because of the nature of the picture, the capabilities of the sensor technology, and some other determining elements like the seasons as well as weather patterns, analyzing and interpreting the qualities of an image may be a challenging task [3]. If it can be solved with the use of deep learning systems, the issue will be critically important for environmental monitoring, agriculture decision-making, or urban planning respectively. As a result, algorithms based on deep learning have been presented in order to rapidly evaluate and understand the remote sensing picture in order to categorize the LCLU. The techniques of deep learning might be used to create either from the ground up or by leveraging networks that have already been pre-trained. On the other hand, there are just a few evaluations of deep learning algorithms that were designed from scratch and learned on pre-trained networks. In this study, deep learning techniques for distant sensing picture categorization are compared and analyzed using CNN-FE, TL, and fine-tuning deep learning techniques as illustration. The purpose of this research is to investigate the feasibility of using a deep learning CNN to classify LCLU data from the Indian Pines dataset, as well as to identify crops in the dataset we have collected. In this study, AVIRIS sensor data from the Indian Pines standard dataset was utilized to classify LCLU images. For this purpose, a study area was established at Phulambri, Aurangabad District, Maharashtra State, India. The EO-1 Hyperion sensor has been used to collect the data at hand. Optimizer, transfer functions, filter size, activation functions, and batch size all have a role in how well a CNN model performs. These settings are used to test how well a DL CNN performs. Deep learning CNN with an optimal value of parameters has also been shown to achieve 97.58% reliability just on the Indian Pines sample and 79.43% efficiency on our survey area dataset. The actual findings prove that CNN is effective in practice even for small-size datasets and unstructured data.

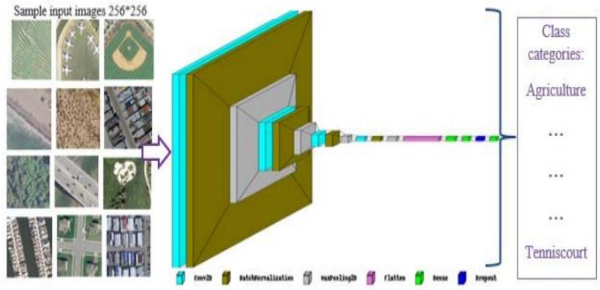

Fig. 1. CNN-FE model layers

VIII. Convolutional Neural Networks for LCLU

In order to characterize surface evolution, analyze global environmental and climatic changes, assist land resource administration, and facilitate regional as well as socially responsible development, the variation of LCLU is the base. The data gathered by remote sensing is, for the most part, available without charge, exhaustive, and user-friendly in relation to the LCLU of the various regions, time ranges, and geographical extents. [2] Throughout the course of the last several decades, a multitude of researchers have classified LCLU using a variety of remote sensing photos. Among the most significant areas of study pertaining to satellite, remote sensing pictures is the development of methods that can conduct LCLU classification both rapidly and correctly. [6] The conventional approach of classifying LCLU data is mostly predicated on visual interpretation and computer-aided picture interpretation. However, in typical supervised classification, the method for extracting a large number of parameters is one that takes a lot of time and calls for a significant amount of expertise [3]. In addition, the standard supervised classification approach based on manually crafted spatial features almost always ends up with an inadequate sample number and poor capacity to generalize the findings. Because there were so few training examples, the precision and reliability of the final classification were severely compromised. To summarize, the manual selection of training instances is an exceedingly labor-intensive procedure that is both time-consuming and has poor repeatability [3]. As shown in figure 2, The sequence

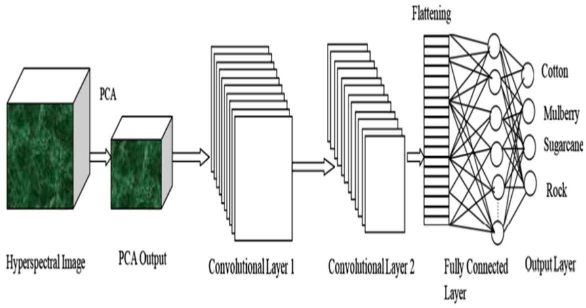

Fig. 2. Architecture of deep learning CNN

of operation, Therefore, a significant amount of work should be concentrated on the selection and selection of training sets in the classification algorithm in order to offer adequate and effective samples in a way that minimizes the amount of time spent on the process. [4]

IX. RF ALGORITHM FOR LCLU

Random Forests (RF) are among the machine learning techniques that are used the most often. This algorithm's rising popularity might be attributed to the fact that it can be employed for the goals of categorization as well as regression, and therefore can be utilized with categories as well as continuous data [14]. A broad variety of Earth science applications, such as modeling forest area, LCLU, including object-oriented cartography, have made use of RF because of its adaptability. Rodriguez did a study in which he evaluated RF to different classifiers. [13] He discovered that RF generated a higher accuracy of 92% than classification trees, which means that RF outperformed classification trees. The improved accuracy of RF was determined to be attributable to its ensemble design, which allows for several classification methods to be trained on separate portions of the learning algorithm. It has been discovered that vector support machines, often known as Support Vector Machine (SVM), perform better than other classifiers owing to their overall great ability to generalize intricate feature sets. SVM was able to obtain rather high accuracy results of 88%, according to the findings of a land cover classification investigation that was conducted utilizing Landsat-8 and that comprised six different land-cover groups [18].

The goal of the Land Cover and Land Use (LCLU) classification project is to classify remotely sensed photographs according to their semantic properties. Improvements in satellite technology have made a large quantity of these very high-resolution images available for use in this categorization assignment. Useful metaphors may be derived from these examples. Due to their profound effects, Deep Neural Networks have recently seen widespread application in a wide range of remote sensing-related advances. Despite this, further progress must be made to improve the generalization and reliability of DNNs in order to attain greater accuracy across a wide range of sensing geometric shapes and categories. In order to find a solution to this issue, we have deployed three distinct Deep Neural Network Ensembles [14]. DNNE methodologies and developing a comparative analysis in order to complete the LCLU classification project. By guaranteeing that the merged models come from a variety of different sources, DNNE makes it possible for DNNs to increase their overall performance. Consequently, this improves the generalizability of the models and results in outputs that are more robust and generalized when used for LCLU multiclass classification. The results of the experiments performed on the NWPU-RESISC45 and AID datasets show that using the collected data from several DNNs results in an improvement in classifier performance, reaches state-of-the-art, and satisfies the requirements [16]

The information gathered by LCLU may also give insights that can be used to address a wide variety of economic and environmental concerns, such as hunger, insecurity, environmental degradation, and the risk of natural disasters. Recent advancements in sensor technology have resulted in the creation of a constellation of satellites and airborne systems, from which a significant quantity of remote sensing imagery with a very high spatial resolution (VFSR) is now available for purchase by businesses. Even when a lot of fantastic chances are presented by Information retrieval and retrieval from VFSR imaging to capture fine-grained LCLU detail is currently immature and expensive. This process is largely carried out by means of conventional field surveys and human interpretation. These kinds of repetitive errands require a lot of physical labor and a lot of time. In the same vein, the state of our environment is in a state of perpetual flux, which necessitates regular updates to the LCLU information in order to facilitate scientific decision-making. As a consequence of this, it is of the utmost necessity to design methods that are both extremely efficient and effective in order to obtain LCLU data in an automated and intelligent manner [18]. During the last two decades, a large amount of work has been put towards automating LCLU classification algorithms by making use of VFSR photos. Both pixel-based, as well as object-based methods, are traditional ways of doing things when it comes to techniques. Through the use of moving kernels or windows, it is possible to incorporate textures and environmental information in order to describe spatial patterns. These methods, on the other hand, are based on pictures with arbitrary structures (such as squares), although in the actual world, things are often asymmetrical in form and organized in a variety of distinct patterns. [18]

X. SVM ALGORITHM FOR LCLU

The choice of an appropriate classifier, in addition to the fundamental units for categorization (pixels or picture segments), is also of the utmost significance when it comes to the mapping of urban LCLU. The achievement of machine learning or ML methods in the categorization of highly complex statistics has massively increased their implementations for RS analysis, and in fact, it has been discovered that these algorithms easily exceed parametric methods in a number of previously conducted RS studies. The GEOBIA-based urban

LCLU directly stated the use of a broad number of ML classification methods, the most prominent of which are ensemble decision tree processors and Support Vector Machinen (SVM). [13] There is a large variety of ML categorization approaches available. In much more recent times, algorithms that make use of deep learning (DL) also had emerged as major players in the LCLU classification space. The categorization of RS pictures has seen recent advances in the form of the development of numerous robust architectures of DL models. This is particularly relevant when using a GEOBIA approach to LCLU classification, since integrating GEOBIA with other prevalent DL approaches, such as convolutional networks, may be difficult. This holds true in the case of CNN-based LCLU class in particular. Some recent research has attempted to draw parallels between DL and more traditional ML methods [14]. The objective of the study was to compare DL's performance to that of SVM in classifying hyperspectral data. Here, a deep sparse autoencoder (SAE) was employed to compete with SVM; SAE is only one kind of DL method. As a result of their research, the authors concluded that SVM was superior to SAE in the vast majority of cases. Additionally, the authors detailed how the greatest accuracies attained using SAE were similar to those generated by SVM. The surprising performance of SAE in contrast to SVM was ascribed by the authors of the research to an inadequate number of labeled samples in the hyperspectral data sources that were taken into account [16].

We test deep CNNs on previously collected remote sensing datasets and then compare the outcomes produced from these tests. We were able to attain an overall accuracy of 98.57% by using the innovative dataset that was presented. The suggested study will result in a categorization system that will open the door to many different possibilities. Applications using earth observation, We show how the categorization method might be used to aid in the enhancement of geographical maps. [2]

The management of natural resources, urban planning, and the evaluation and prevention of natural hazards, for example, all need accurate and up-to-date information on land cover and any changes that may occur. In the field of remote sensing, two of the most important tasks—land cover categorization and change detection—have received a significant amount of attention during the last several decades. The expanding availability of data obtained from remote sensing and the prospect of large-scale automated land cover identification as a result of improvements in computer power and novel techniques to machine learning (ML) seem to be the two primary factors that have led to this concentration.

A strategy for classifying pixels that were acquired is presented in this work employing deep neural networks specifically designed for semantic segmentation of satellite pictures. The generation of land-use and land-cover maps may profit immensely from the use of this methodology. The process of giving global labels to complete scenes is what is referred to as classification purpose [6]. On the other hand, the process of making LCLU maps entails constructing maps by providing a class for each pixel. We demonstrate that it is possible to effectively construct LCLU maps by assigning a number of different LCLU categories to each pixel that is present in a satellite picture. Deep neural networks that were initially trained upon the datasets used during ImageNet large-scale computer vision competition were then fine-tuned utilizing our target data source, which is comprised of Land cover 5/7 multi-spectral images captured in the Canadian province of Manitoba.

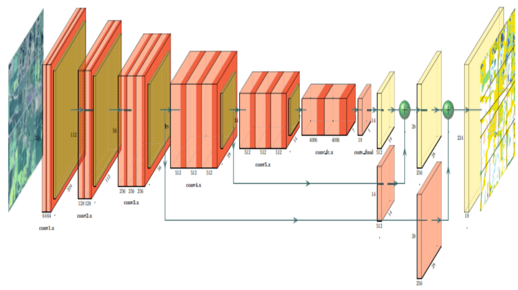

Fig. 3. FCN-VGG: encoder-decoder architecture

This method of LCLU mapping was made possible through the use of these neural networks. This strategy led to an accuracy rate of 88% around the globe. The performance was increased even further by taking into account the cutting-edge convolutional architecture as well as context modules that were combined with the models that were originally used. The end result is a fully automated framework for deep learning that is capable of producing highly accurate LCLU map pictures substantially more quickly than the approaches that are currently semi-automated. This author's contribution consists of significant testing with several FCN architectures with modifications on a one-of-a-kind dataset, a high recognition rate of 90.46%, and a detailed study and evaluation of the correctness of our findings. [6]

Alterations to land use/land cover use may take the form of either the transfer of land to a new kind of use or the growth of an existing land-use type. The usage of land by humans has had a significant ecological footprint, which has led to the need for research and education on the topic. Precise land use and land cover may be put to use in a wide variety of contexts, including apps for monitoring systems, activities involving resource utilization, and planning endeavors. Satellite data are used to create the big coverage-area land use maps that are required to detect and control human activities as well as land biogeography [21]. These maps are produced using a broad area of coverage. Because satellite data are readily available, innovative approaches of mapping land cover with the use of remote sensing data, like Landsat data. Because they've been accessible since 1972, Landsat photos are ideal for use in remotely sensed data. Landsat satellite information is often used to make estimates on the progression of metro regions. In recent years, a wide variety of automated and semi-automatic categorization methodologies have been proposed in order to create an accurate land cover mapping. Classification of images is an essential step in the process of analyzing images obtained by remote sensing [11]. This method is used to classify pixels in accordance with the groupings of surface land cover to which they contribute.

In order to derive information using satellite measurements or to properly categorize LCLU, mathematical techniques are necessary. The strongest features, such as likehood-based and neural networks are not appropriate for use with hyperspectral remote sensing imagery because of the high dimensionality of the dataset and the little number of training pixels and samples available in these classifiers. When it comes to extracting information from spectral images, the spectral angle mapper (SAM) technique is one of the most popular choices. Determining the degree to which the image spectrum and reference reflectivity spectra are spectrally similar is the first step in the SAM supervised classification, which is a technique that allows quick mapping [11]. The reference spectra might either be derived from the images themselves or collected during in-situ investigations using a spectrometer. Both of these options are possible. For spectral analysis that does not exhibit that much resemblance with pixel spectra, it is preferable to derive reference spectra and end members from the imaging itself for the classification objectives. This may be done. However, the most incorrect assumption made when using SAM is the presumption that the end members selected to categorize the image reflect the pure spectroscopy of reference data. SAM is capable of very rapid surveying of the target; however, this presumption is the most incorrect assumption made when using SAM [17].

XI. Analysis and Discussion

The incredible progress that has been made in remote sensing technology has given a rock-solid base upon which researchers from all over the world can conduct investigations into and make predictions about the potentials and services that the cosmos has to offer to those individuals who are relying on the popular revolt to take place and want it to take place. The difficulty of automatically analyzing the data and extracting useful information from it is increased when dealing with enormous volumes of data. In recent years, the expansion of image recognition in remote sensing technologies for low-level in addition to high-level tasks, including de-noising or categorization, has resulted in the availability of a surfeit of land use and cover classification techniques. These algorithms were developed with just a solid theoretical substrate material and therefore are predicated on the both spectral and spatial characteristics of specific pixels. Still, making the transition from pixels to pictures and finally to scenes calls for considerably more concentrated work. The dynamic identification of every pixel or scene is required because in the universe of binary data, no data can be analyzed unless it has been tagged to a specific identifier. This makes dynamic identification of every pixel or scene vital. As a result, one of the goals of a few of the categories is to organize a picture in accordance with a group of semantic categories. The issue is difficult to solve due to the fact that the classification of the land cover into an appropriate category may offer considerable variability, and objects could appear of various sizes and in

TABLE I
LCLU MODELING AS PER PREVIOUS WORK:

Source	Methods used for LCLU	Best method	Survey area	Accuracy for each method respectively
[1]	EVI, RFC	RFC	South Dakota, Northern Great Plain, US department of education	84,95
[2]	CNN.	CNN	European Urban Atlas	98.57
[3]	DBM,CNN	CNN	Ontario, Canada	86,94.3
[4]	Neural-fuzzy models,CNN	CNN	Phulambri, Aurangabad, MH, India	97.58, 79.43
[5]	CRF model, FCN	FCN	Province of Manitoba in Canada	88, 90.46
[6]	CNN-FE, TL	CNN	University of California Merced	82.04,84.4
[7]	DL ,CNN	CNN	church, seashore, wetlands, meadow, middle neighborhood, thermal power plant, trailer park	90.03, 92.11
[8]	CNN–MRS	CNN–MRS	Golcuk region in Kocaeli, Turkey Istanbul test site area	92.03
[9]	MLP,CNN	CNN	Southern England, North West England	82.01,83.32
[10]	deep learning model, CNN	CNN	China	92.23,99.97
[11]	CNN-FE, DL,CNN, pre-trained models,	CNN	China	81.2, 81.3, 81.4, 79.7
[12]	CNN AlexNet, VGG-16.	VGG-16	Egyptian north-eastern region	90,94.6
[13]	RF, SVM,SAM	RF	India (Delhi)	88 , 69.43,61.30
[14]	SVM, RF	SVM	Uppsala , south-central Sweden	73.3,75.8
[15]	Hybrid model	Hybrid model	Kerala, India	75.09
[16]	SVM, RF	SVM	New Delhi, India	78.32,89.43
[17]	RF,CART	RF	Australia, USA	96.69,82.83
[18]	RF,GB,SVM,MLP	MLP	Illinois, USA	92.04,92.87 ,92.45,93.64
[19]	LSTM,FCM	LSTM	Saxon Switzerland	84.8,81.8
[20]	MLR	MLR	India	98.5
[21]	CNN	CNN	Forest, highway, Lake, sea	99.17
[22]	VGG19	VGG19	Urban areas	99.64

different directions. Another difficulty that we often see is that the same land cover and sometimes even the same items may be observed in imagery that is associated with different classifications [12].

Several of the reasons that environmental monitoring programs are a must include the consumption of resources, the rise in population, the movement of people to urban areas, and the progression of drought conditions and maintained with consistent production and revisions. The use of artificial intelligence within the geospatial area of Environmental and current land monitoring operations is another difficult problem to solve. In this investigation, land cover, as well as land use mapping, was carried out by using the CNN–MRS model that was developed [13]. The CNN–MRS model was comprised of two primary stages: the first stage was a CNN-based land use/cover categorization, and the second stage was an enhancement of the classification using a spatial filter and MRS. In the first experiment, many different patch sizes and a variety of band numbers from the Sentinel-2A images were employed. The algorithms were analysed and scored according to their overall accuracy, resolution, and kappa coefficients. The suggested method had the greatest overall accuracy, with scores of 97.31 percent in the Istanbul test site region and 98.44 percent in the Kocaeli test site area respectively [13].

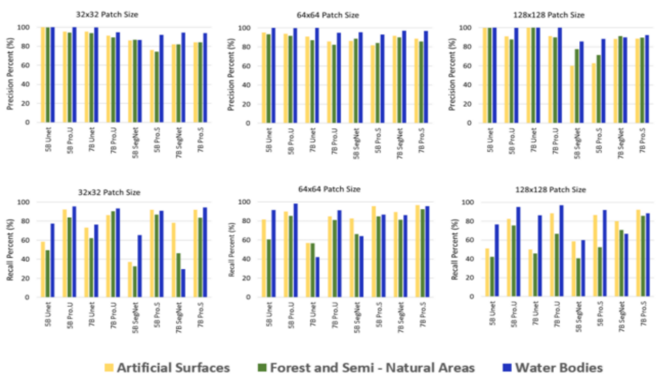

Fig. 4. Precision and recall values of different patch sizes

The accuracy of the CNN–MRS model was shown when it was applied to the process of producing land cover maps over broad regions by the findings. The McNemar test was used in order to evaluate the relevance of the models that were applied. Experiment 2 used the Zurich Summer dataset, and the results showed that the suggested method had an accuracy of 92.03% altogether. Quantitative comparisons are made between the findings of this study and those of comparable research including state-of-the-art CNN models [14].

The most successful model is believed to be CNN. Convolutional neural networks (CNNs), which represent a kind of network infrastructure for deep algorithms, are well suited for applications such as image recognition and other jobs that need the understanding of pixel input. These kinds of tasks are suitable for CNNs. Convolutional neural networks (CNNs) are still the network architecture of preference when it comes to detection and recognition; however, there are various other types of neural network models that are employed in deep learning. One of the benefits of employing these models is that CNNs have the capacity to create an internal representation of a two-dimensional image, which is among the advantages of using these models. When dealing with photos, it is essential that the model be able to understand the location and scale of the many structures that are included in the data. This is made possible by the previous point. CNN layer, which is comprised of a few different filters and is used to accomplish the convolution function.

XII. LIMITATION

Deep CNN models have the capability of building RS pictures in three different ways: by starting from scratch, by employing pre-trained algorithms, and by updating the pre-trained concepts. The pre-trained classifiers are based using models that were trained previously on other huge datasets, such as photos from the ”imagenet” project. Because RS photos exhibit inconsistent qualities in comparison to the ”imagenet” data, it is possible that training DL models by employing a pre-trained network might have constraints for the classification of RS images. Additionally, it is possible that the pre-trained Convolution layers will have limits when it comes to the extraction of RS image characteristics owing to the differences between the attributes of natural pictures and RS images. Consequently, developing deep Convolutional networks from the ground up might be a solution to such limits. On the other hand, there has not been a lot of research done in RS yet on the process of training deep Convolutional networks from start. It’s possible that this is why developing Neural network models from start is so challenging; there isn’t enough detailed training data, and the training process takes a substantial amount of time.

XIII. CONCLUSION

The mapping of LCLU changes and their implications at regional and local scales serve a broad range of objectives to manage and prevent a variety of natural catastrophes, including landslides, urban floods, and global climate change, amongst others [16]. The study of change detection has a detrimental impact on meteorological patterns, the vulnerability to hazards, the decline in biodiversity, as well as the global and regional socio-economic processes. It has been seen all around the world that diverse land coverings are being changed into new land-use patterns at such a rapid rate. Differences in land cover are mostly caused by population increase in a region, as well as other variables like as human interference, agricultural needs, natural disasters, the growth of the economy and urbanization, and other things. Concerns regarding LCLU first appeared in study fields once it became clear that the land surface exerts a significant amount of effect on the global ecosystem. The availability of data about shifts in land use is beneficial to the process of decision-making regarding environmental management and preservation. The capability of CNNs to generate an internal model of a two-dimensional picture is one of the advantages of utilizing these models. When dealing with photos, it is essential that the model be able to understand the location and scale of the many structures that are included in the data. This is made possible by the earlier point. The number of parameters that a CNN needs to learn is noticeably smaller than that of multi-layer neural network models. This is because the number of items in a CNN is substantially lower than that of an MNN, which in turn reduces the likelihood of the network overfitting itself.

XIV. FUTURE WORK

In recent times, the communities of machine learning and remote sensing have started to connect owing to concurrent reasons as a result of developments in both fields. First, well-known contests in the field of data science, which are becoming more common, have shown excellent classification accuracy by making use of sophisticated machine learning algorithms. We came to the conclusion that the system that was built has the potential to improve the effectiveness of the currently time-consuming process of land cover categorization, which will aid in the expedited updating of land cover maps. The Convolution neural land cover classification algorithm that was created classifies land cover on such a pixel unit, which might be distinct from the real land usage of the parcel unit. Therefore, including land parcel limits into sensor land cover may significantly increase the accuracy of the classification, and as a result, this issue will be the subject of more research in the near future.

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