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Efficient Classification of Satellite Image with Hybrid Approach Using CNN-CA

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Abstract

Today, satellite imagery is being utilized to help repair and restore societal issues caused by habitats for a variety of scientific studies. Water resource search, environmental protection simulations, meteorological analysis, and soil class analysis may all benefit from the satellite images. The categorization algorithms were used generally and the most appropriate strategies are also be used for analyzing the Satellite image. There are several normal classification mechanisms, such as optimum likelihood, parallel piping or minimum distance classification that have presented in some other existing technologies. But the traditional classification algorithm has some disadvantages. Convolutional neural network (CNN) classification based on CA was implemented in this article. Using the gray level Satellite image as the target and CNN image classification by the CA's self-iteration mechanism and eventually explores the efficacy and viability of the proposed method in long-term satellite remote sensing image water body classification. Our findings indicate that the proposed method not only has rapid convergence speed, reliability but can also efficiently classify satellite remote sensing images with long-term sequence and reasonable applicability. The proposed technique acquires an accuracy of 91% which is maximum than conventional methods.

Keywords: Soft computing, Satellite image, CNN, Cellular automata and classification.

1 Introduction

In recent years, academics throughout the world have focused on image categorization as a vital tool for pattern recognition and computer vision. Digital imagery makes up the vast bulk of satellite images. An image processing approach may be used to extract the right information from the photos that have been saved. This technique may be used to enhance visual perception and to repair or change the picture depending on graphic distortion, image blurring, or degradation. There are only a few ways to analyze an image, and they all rely on the nature of the issue. Image segmentation and classification algorithms may be used in a number of ways to categorize images. Four types of image classification may be distinguished depending on how they approach the problem, including clustering, edge-based, region-based, and model-driven approaches. The CNN is now the most used image classification procedure because of its simple concept, fast estimate, and great classification impact. One of the most complicated paradigms in data science is cellular automata. It has strong parallel processing resources and a broad understanding of time and space and can efficiently model the complex system's spatiotemporal dynamic evolution process. It has been commonly used in traffic problems, human relocation, environmental monitoring, etc. The initial implementation of the CA model was in the 1940s. Nevertheless, its use is still less in the area of image processing and the accomplishments are still insufficient. Image classification can be accomplished by optimizing the similarity between artifacts grouped into the same cluster and reducing similarities between the various clusters. It has simple calculation and high speed characteristics and is able to effectively solve the complexity and confusion of image processing. However, when the images are normally classified by a single CNN, it is possible to get stuck in a local maximum, the boundary becomes blurred and the untidy boundaries and bad visual effects are shown. Convolutional Neural Networks (CNNs) with Cellular Automata's (CAs) have been suggested in this study to classify pixels based on a combination of spectral and contextual data information, and so the classification results are enhanced over traditional approaches. Due to the improved performance, we may conclude that CA-based spectral and contextual images are more accurate for the CNN. The following are some of the main points of this research: Using a convolutional neural network, satellite photos may be analyzed for information. In order to classify high-resolution satellite pictures into two categories, the convolutional neural network is used to separate it from the band values into features, and to preliminarily extract the band selection values. For the remainder of this work, the sections are as follows: Several more methods for analyzing satellite images are discussed in Section II. According to Section III, the categorization issue is shown in detail. Cellular automata categorization using CNNs is shown in Section IV. Section V exhibits the experimental verifications, whereas Section VI illustrates the conclusion.

2 Related Works

As an example, in [1], the author presents an explanation of the concept of satellite pictures and remote sensing, as well as a quick summary of the prior work in that field. This page describes existing research on the use of Alwar satellite imaging methods, which have covered acceptable land coverage elements such as vegetation, rivers, metropolitan areas, barrens, and rocky regions, as well as other relevant land coverage features. The classification algorithms' postage is determined by the classified file, which displays multiple classifications displayed in different colours and allows for easy identification. Every function is denoted by a different colour and may be more detailed. [2] examines and assesses the different categorisation algorithms in terms of overall performance. Binary logistic regression (BLR) is provided in [3] as a simple and reliable technique for picture classification. A subtropical east coast area of India was chosen as the location for the study, which encompasses land, fallow land, woodlands, and water, as well as land and water. The categorization method made use of ArcGIS, Excel, and R from Microsoft Office. Along with BLR training and testing data, the R classification was used for random forest analysis, which also included BLR training and testing data. A variety of strategies for categorising artefacts in remote sensing scenarios may be utilised, with various image processing techniques used. To identify pictures, the HDCA suggested in [5] used texture and spectral properties in two iterative additional code steps: (1) mixing operators, and (2) moving and departing operators, respectively. operators Specifically for the HDCA, a new concept was developed: the weighted gap from Manhattan. This paper describes a novel k-mean optimization approach that is utilised for the purpose of picture categorization (see [6]). Two alternative activation functions have an impact on the accuracy of classification in an artificial neural network, according to [7]. The Wideband Imaging Spectrometer's visible and near-infrared scales are used for performing categorization procedures. According on how they were preprocessed (e.g. MDC, MLC), Spektral Angle Mapping (SAM), and Support Vector Machinery (SVM) algorithms are used to evaluate images (SVM). Computer algorithms sort photos into several categories depending on what's shown in them. Uncertainty matrices are used to verify the classification findings. In [9], a CNN is recommended for satellite applications to locate individual autos. A CNN beat an FSM in the job of exterior object recognition utilising Land sat 8 photos, according to a study in [10] that used a CNN with a Support Vector Machine (SVM). Using cellular automata in the background and a hierarchical framework, [11] offers a categorization of satellite pictures. Cellular automata in the background and the hierarchical structure of satellite images were employed to classify them. Image processing techniques for urban tree canopying identification were shown using high-resolution satellite images in [13]. Each pixel's probability of being present may be calculated using the approach provided by [14]. In order to assign a pixel to the appropriate class, values are compared. The use of this method for classifying satellite photographs, particularly multi-spectral images, is very successful. There is a cost, though, in terms of processing power. The Sparse SVM classifier was developed in [15] and is described in detail. In order to categorise the segmented images, they are broken down into little sections. After the data is extracted, picture patches and sparse pictures are applied to it. Following this, a sparse image is resolved utilising the verified image pixels and optimised for classification efficiency. With multispectral orthoimagery and the digital surface model, a convolutional neural network (CNN) may be used to identify a tiny city with high accuracy and speed, according to [16]. (DSM). Segmentation is improved by using low-level pixel class predictions to enhance high-level segmentation. They examine and critique a variety of CNN architectural design options in their paper. Similar per-pixel classification efforts on different land regions with the same set of categories as the researched land region are compared to see how accurate the classification is (vegetation, ground, roads, buildings, and water). Based on this research, they can safely conclude that CNNs can be used to solve both the remote sensing data segmentation and the problem of object recognition.

3 Problem Statement

There are several challenges to overcome, including not only gathering images but also processing and disseminating the information quickly and accurately so that the intended target detection and classification may be achieved. The first step in solving any satellite target identification challenge is to separate the relevant components from the rest of the image. The robust satellite target detection system nevertheless faces a challenge in classifying objects. Guards and debris are hard to come by in this area. For this reason, a new and improved satellite image categorization method is needed.

4 Proposed Methodology

In this section, the proposed scheme has been gone through for training a CNN for satellite image classification and also a new approach to develop CNN features extractions from the trained data which was represented in figure1. Corresponding to the digital satellite image, each image pixel can be called a cell in the CA model, and then the whole image is a cell area. It often includes cell area, cell location, cell neighbor, and evolutionary law. The cell neighbor can be identified as a cell adjacent to a cell in space, and the area consisting of all the neighboring cells is called its neighborhood. Evolutionary rule means the laws that decide the status of the cell at the next moment according to the existing cell and its environment, and further change and improve the relationship between the cells. Sometimes it's often called the state transition feature, and it's the key to the whole CA model.

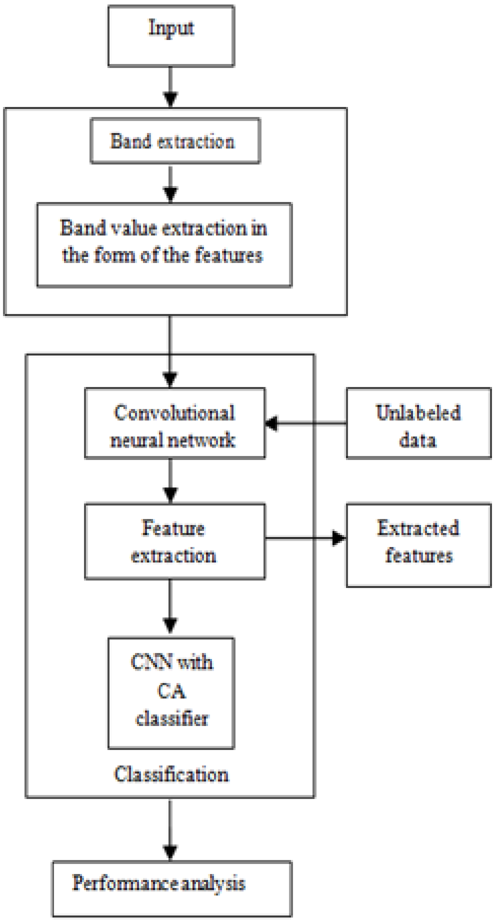

Figure 1: Schematic representation of the proposed methodology

4.1 Dataset description

The Indian Space Research Organization has developed a web-based tool that enables users to access a variety of mapping-based material. Bhubaneswar (lit: Earth) The programme is only available in four regional languages, and it is mostly focused on India. Satellite and ground data from the Indian Space Research Organization (ISRO) is also included in the collection. Bhuvan has a reputation for working with a wide range of government agencies to leverage geospatial data. Bhuvan has enabled the Indian government to host geospatial data as visualisation and use knowledge layers since its inception. Toll information systems, islands, and cultural heritage sites are all included as examples of different geographic layers that might be defined. Crowdsourcing or Indian government sources are used to acquire network information. In other words, it's India's counterpart to Google Earth, with the sole purpose of delivering free, high-resolution images of India. Hyperspectral data is the most common kind. Indian geospatial data service Bhuvan is a software programme with several add-on options. It provides a two-dimensional and three-dimensional view of the Earth's surface. With material in four Indian languages, the browser is specifically designed for the Indian market. India's multi-sensor IRS (Indian Remote Sensing) satellites have been providing Bhuvan with imagery since August 12th, 2009. Various spectral, geographical, and temporal resolutions of free data sets, services, and applications are accessible. Navigating in a 3D environment with a resolution of 5.8 metres to 1 metre is possible with the web-based mapping service. There is no browser or operating system that Bhuvan doesn't work with. Plug-ins aren't necessary in the current version. Registration is required only when downloading satellite data with a resolution of at least 25 metres, such as the NDVI and OHC datasets. Data may now be accessed on the go with the Bhuvan mobile and android applications.

There are two ways to express a CA with a CNN in this case: Once each neighborhood's matching distance input instances have been identified, an association between each neighborhood and an appropriate output pixel is carried out following feature extraction. As we explain in Section 5.1, we first apply a single convolutional layer, then repeat 11 convolutional layers to represent any CA. To achieve the proper weights instead of training using an algorithm based on a study of CA data, one might do an in-depth investigation of the CA itself. Many additional representations exist, and we show that a particular way provides a deep learning network that uniquely matches each of the matching distances, which differs based on the feature being matched. When the landscape input is compared to a ground truth using a single nonunity convolutional layer, the network may be trained using just one layer. These convolutional neurons have a receptive field that extends around the CA. Convolutions in the next layer do not incorporate any additional neighbor information from the previous layer. CA rule table logic is based on current research showing that convolutional layers may dramatically enhance network expressiveness while using just a little amount of processing power. Since the CA is local, no pooling layers are needed in the network, hence a tiny convolutional layer may be added to it. There are some similarities between this method and others that have attempted to parallelize basic processes like binary arithmetic, but there are also some significant differences.

4.2 Feature extraction

An efficient method for reducing the size of an image is band extraction. It makes use of spectral correlation to accomplish data compression. The spectral bands are prioritized using CNN. Each class's eigenvalues and eigenvectors are tallied, and a loading factor matrix is generated as a result. Each band's discriminating power is shown in the components of this matrix. Discriminating power is reduced in favor of higher priority bands. Because CA decreases the distance inside a class, but also increases the distance between classes, it is superior than other strategies. Here the feature that can be extracted by a CNN Color characteristics are less influenced by image format, direction, and point of view, and have high robustness and objectivity. It has historically been commonly used in the production of pictures. And the color features are usually represented by a histogram of color. The loading factor associated with each spectral band determines which bands are prioritized. The process of the feature extraction can be represented in the equation (1) Where R is a histogram, P(x,y) is the

$$R_a^b = \sum_{a=1}^{B_c} \delta(P(x,y) - a) \qquad (1)$$

pixel of the co-ordinate (x,y) ,B_c is the interval number of the histogram, a represents the constant. The histogram includes the mean value and eigen covariance of each pixel in the geographic space that can easily supplement the spatial distribution details of absent pixels in the histogram. Similarity of histograms can be determined by, Where Ø_a is the spatial similarity.

$$\mathrm{p}(p_a^s, q_a^s) = \sum_{a=1}^{B} \text{Ø}_a \mathrm{p}_n\ (n_a, n_a') \qquad (2)$$

CNN is an unsupervised classification approach focused on the optimization of objective functions.

Where n_a is the total number of the pixel at a regular interval, μ is the normalized constant, $\mathrm{p}_n\ (n_a, n_a')$ is the similarity of different intervals of the spatial histogram and,

$$\mathrm{p}_n\ (n_a, n_a') = \frac{\sqrt{(n_a, n_a')}}{\sqrt{(\sum_{j=1}^{B_c} n_{ij}) * ((\sum_{j=1}^{B_c} n_{ij})^{\wedge} r)}} \qquad (4)$$

If the image X= x1, x2,..., xn is a set of n pixels, xj is the image pixel's own name, c is the number of groups, and V= v1, v2,..., vc is the cluster array. Let the objective function of Jm fulfill the restriction Where m is the weighted index. Discriminating power of each band is computed as, In order to reduce the size of the feature, bands with a greater discriminating power might be chosen. The objective function of I is to apply the squares of the weighted distance to the respective cluster centers from the image pixel points. The smaller the size, the closer the center and the greater the cluster effects are to the pixels. Finally the feature matrix are obtained. Here, the final feature has been extracted

$$\sum_{i=1}^{c} R_{ij}m = 1\left(R_{IJ}\Sigma|0,1|\right): \quad (5)$$

$$J_M=\sum_{i=1}^{c}\sum_{j=2}^{n} R_{ij}m\,\mathrm{d}^\wedge 2\;(x_i, v_j) \quad (6)$$

$$Feature\ band\ power = \begin{cases} I \sqcup \mid objective \rightarrow \ Cell_{Power} - 2 \\ j == I \rightarrow \ Cell_{feaature} + 1 \\ j! = I \rightarrow \ Cell_{bandwidth\ discrimination} - 1 \end{cases} \quad (7)$$

by the nearest values of each pixel and it helps to reduce the feature length. The classifier is trained using a mix of texture and spectral features. Finally the precise features can be extracted so that the feature length gets gradually reduced.

4.3 Proposed CA with CNN

Neural networks trained on time series of cell automata pictures may be used to learn their rules, as shown by the analysis of convolutional perceptrons with restricted layers and units. We used random pictures and CA rulesets to train ensembles of convolutional neural networks, which we found to be successful. We will create a CA in this part, which is defined as an explicit mapping between each of the three 3x3 pixel groups in the binary picture and an output value. When we apply this map to the training data, we end up with a new binary image dataset that is a collection of random binary images (the training labels). We guarantee that each rule is reflected in the training data by using big enough pictures (10x10 pixels) and batches of training data. To ensure that each of the 100 possible states has an equal probability of occuring, images that are big enough have an equal number of black and white pixels. When just one rule is shown at a time, the network training process advances significantly faster than when several rules are shown. Displaying all input instances at once promotes rule representations to be learned based on their relative importance in terms of maximising accuracy, which is advantageous for increasing accuracy. The network structure is highly impacted by the sequence in which individual rules are shown. The loss function and hyperparameters were used to train the networks (learning rate, initial weights, etc.). A fresh validation dataset was created for each degree of hyper parameter adjustment since it is computationally cheap to produce new training data. For the first time, random CA rulesets were used in order to verify that network hyperparameters were not being adjusted to particular CA rulesets. Validation datasets were generated using the same CA ruleset as the training dataset, except they were 20% smaller in size. When the network's prediction accuracy on the secondary validation dataset achieved 100% after the predictions were rounded to the closest integer, training was ended. The optimizer utilised a loss that was not rounded appropriately in order to calculate gradients. A fresh dataset of previously unknown test data was used to put the final, trained networks to the test (equal in size to five batches of training data). All of the CA rule sets that were put to the test benefited from the use of an architecture based on convolutional networks, which was specifically developed to make learning the whole rule table easier. In order to study the internal representations of CA rule sets using CNN, we emphasise that 100% performance on the second validation dataset is a prerequisite for terminating training. CA ruleets differed widely in terms of training duration and dynamics, but the results indicated that the performance of all trained networks was equal (discussed below). It is called multiphase function learning when several CNN models are used in tandem and then combined into a single fully connected layer with varying contextual input sizes. CNNs of different sizes are shown next to Depth L on the right. Repeating this technique results in a chain of CNN layers that are linked to each other. Finally, this categorization input is included in the completely connected layer's hidden layer. The extracted feature and the class value are the input of the CNN which has experimented a multilayered CNN. For the purpose of the classification when n features rely on condition, the measured likelihood values of each function are then attached to a standard distribution and their result is finally taken after normalization.

Where F is the feature of the image.The weighed features. Finally, the classification was performed with the structured image on the basis of CNN. The CNN continually updates all the weighting

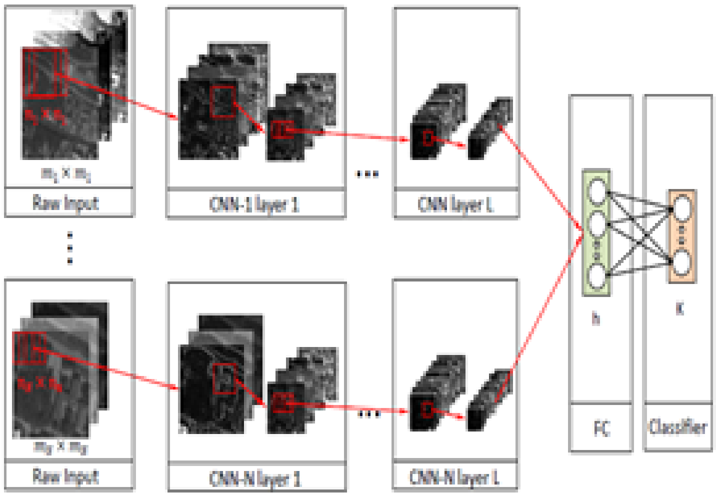

Figure 2: Classification on CNN

$$p\left(x^1 \ldots \frac{x^n}{y}\right) = \prod_1^n (p(x^i/z) + \beta^i u(x)/1 + \beta^i u(x)/1 + \beta^i \quad (8)$$

Where β^i the uncertainty value of (I) is, $u(x)$ is the uniform distribution function and n is the number of the image features. Then we allocate the corresponding weight values to various functionalities and the images can be represented with the following equation with the latest comprehensive feature,

$$F=[\alpha * F_1, \beta * F_2] \quad (9)$$

characteristics and eventually achieves a high-precision image classification. After the classification, the CNN result has been classified by CA, by checking some rules in patch by patch, in each patch getting (3 X 3) matrix.

Rule 1: If the current pixel's spectral values are incorrect, the current pixel has the erroneous number of classes: [class] [type] [quality] = majority class of the neighborhood, iteration, and loudness. '

Rule 2: For example, if the number of classes is one and all of the neighbouring class states are either empty classes or those of the current pixel's class, the following rule applies: [class] [type] Classification, iteration, and concentration = quality.

Rule 3: Any neighbouring class state that is distinct from the current pixel class, then: [class] [type] If there are just one class and the current pixel class differs from any of the neighbouring class states, then: Class, iteration, and edge each have the following qualities:

Rule 4: When there are more than one classes, the following steps are taken: [class] [type] Pixels may be divided into four categories: (Quality) = the majority class in the neighbourhood among the questionable classes, iteration, unknowable, unsure, noisy, edge, and focus (pixels that are not uncertain, noisy, or edge).

For classification by triggering the neuron, we begin the cycle,

$$P_j^1 = \sigma \sum_K x_{jk}^1 c + b_j^1 \tag{10}$$

The filter can be used will rescale the errors. The equation can be written in the form of error free vectorised form,

$$b_j^1 = \sigma(x^l c^{l-1} + b^l) \tag{11}$$

The quadratic set in which the training set can be merged,

$$q = \frac{1}{2} \|Y - c^l\|^2 = \tag{12}$$

The gradient output is given by,

$$\frac{\partial C}{\partial w_{kj}^l} = ck^{l-1}\delta_j^l \quad =c \tag{13}$$

$$F = \det[p] - k\left(\text{classify}(p)\right)^2 \tag{14}$$

Where p is the feature. These are to be declared as

$$\det[p] = a_j^l b_j^l \tag{15}$$

$$\text{classify}(p) = \quad c_j^l b_j^l \tag{21}$$

The CNN classification was concluded as

$$F = a_j^l b_j^l - m\left(c_j^l b_j^l\right)^2$$

(16)

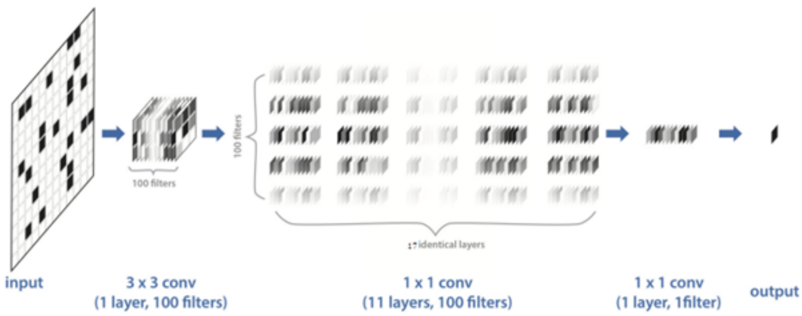

Figure 3: Architecture of CNN-CA

The overall suggested architecture was illustrated in figure 3.

4.4 Quality Calculation

In order to avoid misunderstanding, this approach uses two images (one that has been expertly categorized and one that has not been) and builds a confusion matrix. This highlights the critical role that precision in cellular automaton categorization plays throughout the process. This function also provides a list of pixels that have been erroneously classified and have merged with the class, which has been classed using this method.

5 Result and Discussion

The Indian Space Research Organization's Bhuvan (lit: Earth) mapping-based material has been used to test the findings. In addition to allowing viewers to explore 2D and 3D photos of the Indian subcontinent, Bhuvan also provides information on soil, wasteland, and water resources. Admin borders may be superimposed on photographs according to the user's preference from a list of accessible boundaries. Bhuvan's AWS (Automatic Weather Station) data may be shown in both a visual and tabular manner. The 3D view pop-up menu allows users to "fly" from one area to another (with fly-in, fly out, jump in, jump around and view point controls). Navigating around the app is done using a heads-up display (HUD) (tilt slider, opacity control, compass ring and zoom slider). It's possible to make items in 2D (such as text labels and rectangles) and 3D (such as polygons and circles) by using the drawing tool (placing of expressive 3D models, 3D polygons and boxes). Images and distances may be recorded using snapshots (which are stored to a floating window and can be saved to an external file) and measuring tools (horizontal distance, aerial distance, and vertical distance).The sun's position may also be correctly adjusted for a specific time of day, allowing the viewer to see the landscape as it would seem at that time of day, with realistic shadows and lighting as a result. About 100 input images are taken. Overall, it has a pixel value feature of every band where there are 200 bands in each image. The overall simulation was carried out in a MATLAB environment.Here the 17 layered CNN- CA is experimented in the practice. Further, the proposed work of CNN with CA is compared with the other existing methodologies. The fundamental truth of a satellite image is presented in

Figure 4: Labeled satellite image 1

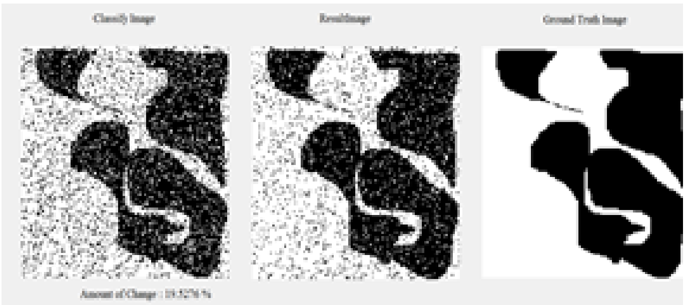

Figure 5: Ground truth and classification using CNN- CA

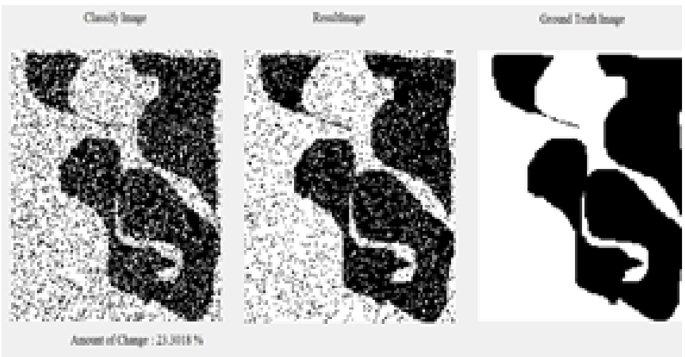

Figure 6: Ground truth and classification using K-nearest neighbour (KNN) CA

above figures that represent the information which is collected at a certain spot. This allows real-life objects and content on the ground to be connected to satellite images. This knowledge is widely used for remote sensing data analysis and correlates the findings to the basic truth. Our proposed

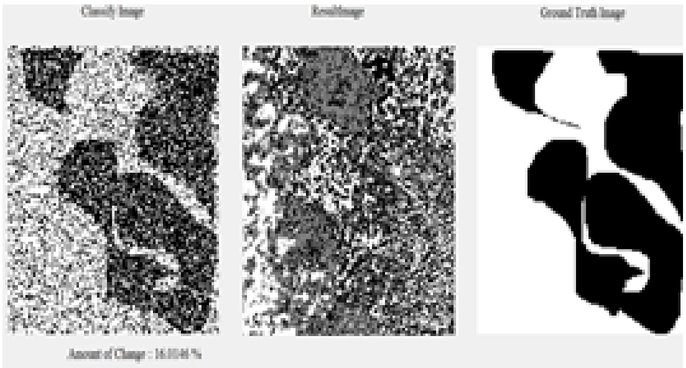

Figure 7: Ground truth and classification using Minimal distance (MD) CA

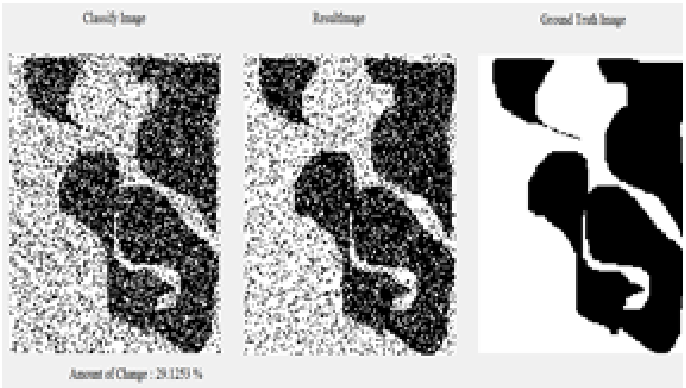

Figure 8: :Ground truth and classification using Parallel piped (PP) CA

CNN-Cellular Automata pipeline can divide the object is divided to super pixels in different sizes and the pixels are chosen as seeds to disperse the backdrop at the boundary of the picture. In order to obtain deeper functionality (CNN) are then used as feature extractor. The previous map and deep functionality created are both applied to the single layer CNN-cellular automata. Finally salience maps integrate these in order to reach our last result. Here the proposed methodology is compared with the 3 other existing technology when compared to that CNN-CA outperforms well and classifies the labeled image 1 precisely as depicted in [5-8].

The training error is the error we receive back when we apply the trained model to the training data. Keep in mind that this data has already been used to train the model, and this does not always imply that the model once trained will properly perform when applied back to the training data The mistake we obtain when we run the trained model on data that it has never seen before is called a "test data error.". The model's precision may frequently be gauged using this information. Figure 8 shows the results of the suggested approach in action, and the picture quality is excellent. Here, the training error is generally lower since it is based on data used to fit the model, rather than on data used to test the model. In this case, a trained model is likely to overestimate its training error based on the training data.

The performance analysis depicts that CNN-CA outperforms well when compared to the other existing methodologies because the image quality obtained will be good was clearly depicted in figure [11-15] and table 1,2.

6 Conclusion

CNN-CA is used to classify satellite photos in an innovative way. In combination with photos and the CA's self-processing, the initial clusters and segmentations are improved in both speed and accuracy. Ca has been shown in experiments not only to be an effective picture protector but also to enhance the intensity attributes. Using the recommended strategy, a long-term series classification

Table 1: comparative analysis of performance parameters

			EXISTING					
Parameters	**PROPOSED**		**KNN**		**MD**		**PP**	
	CNN	**CNN WITH CA**	**KNN**	**KNN WITH CA**	**MD**	**MD WITH CA**	**PP**	**PP WITH CA**
Accuracy	0.8637	0.9175	0.8363	0.8989	0.7479	0.7714	0.8024	0.8455
Error	0.1363	0.0825	0.1637	0.1011	0.2521	0.2286	0.1976	0.1545
Sensitivity	0.8449	0.9076	0.8162	0.8858	0.7203	0.7474	0.7794	0.8274
Specificity	0.8809	0.9263	0.8547	0.9106	0.7738	0.7935	0.8236	0.8619
Precision	0.8662	0.9160	0.8368	0.8986	0.7496	0.7689	0.8028	0.8442
False Positive Rate	0.1191	0.0737	0.1453	0.0894	0.2262	0.2065	0.1764	0.1381
F1_score	0.8555	0.9118	0.8264	0.8922	0.7347	0.7580	0.7909	0.8358
Matthews Correlation Coefficient:	0.7268	0.8344	0.6718	0.7971	0.4951	0.5417	0.6039	0.6901
Kappa	0.7266	0.8343	0.6716	0.7970	0.4947	0.5415	0.6037	0.6900

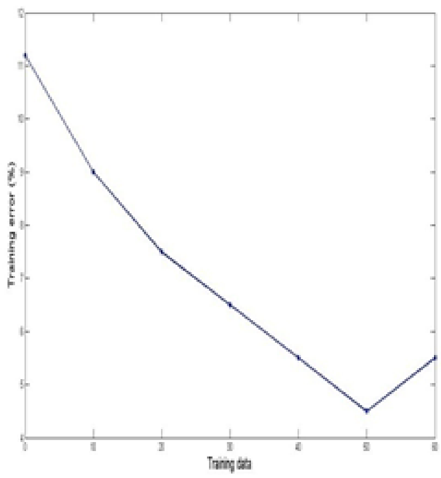

Figure 9: Training error Vs. training error

of the Remote Sensing Image was applied and addressed, and excellent results were produced when compared to other current approaches. The suggested method has a 91 percent accuracy rate, which is much greater than that of current methods.

Declaration: Ethics Approval and Consent to Participate: No participation of humans takes place in this implementation process

Human and Animal Rights: No violation of Human and Animal Rights is involved.

Conflict of Interest: Conflict of Interest is not applicable in this work.

Figure 10: Labeled satellite image 5

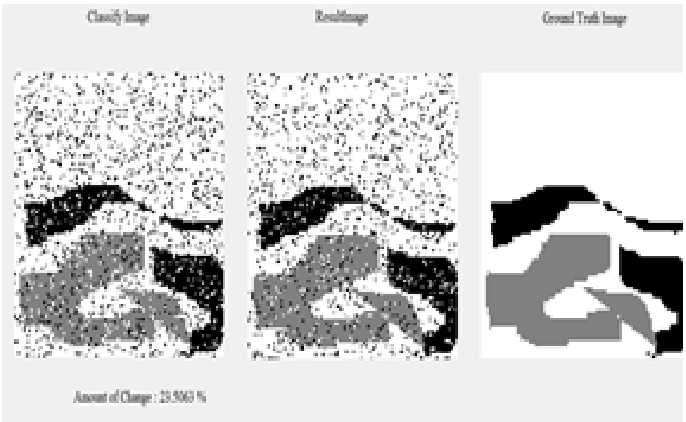

Figure 11: Ground truth and classification using CNN- CA

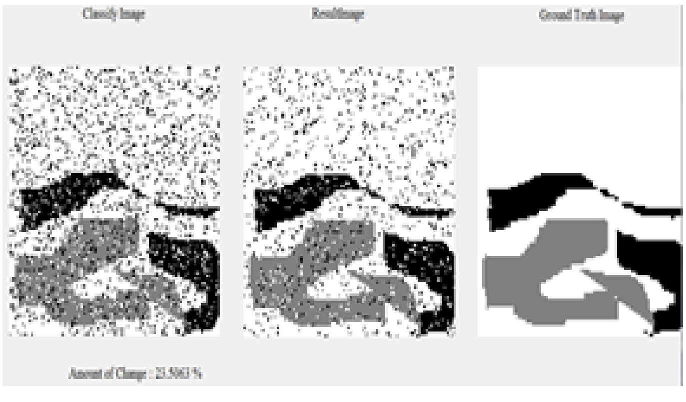

Figure 12: Ground truth and classification using KNN- CA

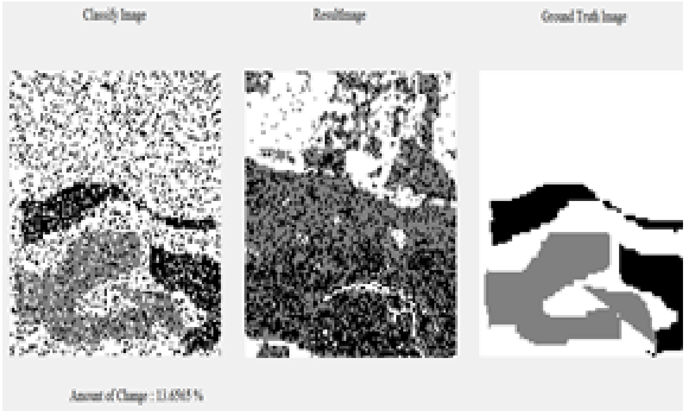

Figure 13: Ground truth and classification using MD- CA

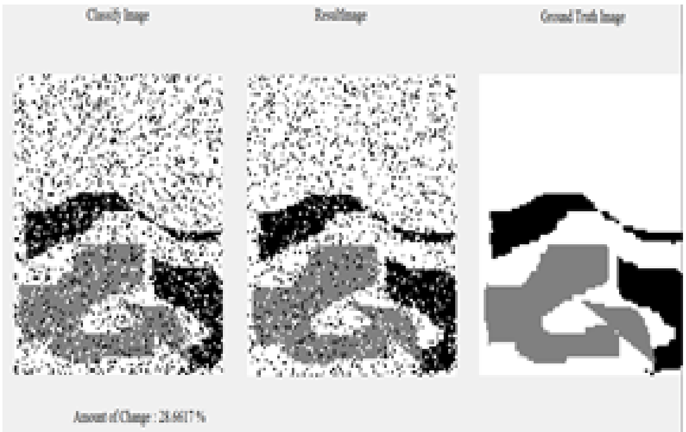

Figure 14: Ground truth and classification using PP- CA

Table 2: comparative analysis of performance parameters

			EXISTING					
Parameters	**PROPOSED**		**KNN**		**MD**		**PP**	
	CNN	**CNN WITH CA**	**KNN**	**KNN WITH CA**	**MD**	**MD WITH CA**	**PP**	**PP WITH CA**
Accuracy	0.8594	0.8815	0.8367	0.9028	0.7490	0.7801	0.8175	0.8477
Error	0.1406	0.1185	0.1633	0.0972	0.2510	0.2199	0.1825	0.1523
Sensitivity	0.7821	0.8086	0.7531	0.8408	0.6565	0.6882	0.7287	0.7655
Specificity	0.8983	0.9126	0.8850	0.9263	0.8372	0.8531	0.8745	0.8919
Precision	0.8598	0.8820	0.8353	0.9017	0.7463	0.7749	0.8150	0.8458
False Positive Rate	0.1017	0.0874	0.1150	0.0737	0.1628	0.1469	0.1255	0.1081
F1_score	0.8134	0.8390	0.7847	0.8675	0.6843	0.7178	0.7605	0.7968
Matthews Correlation Coefficient:	0.7322	0.7705	0.6928	0.8084	0.5531	0.5988	0.6611	0.7111
Kappa	0.6837	0.7334	0.6326	0.7813	0.4352	0.5053	0.5894	0.6574

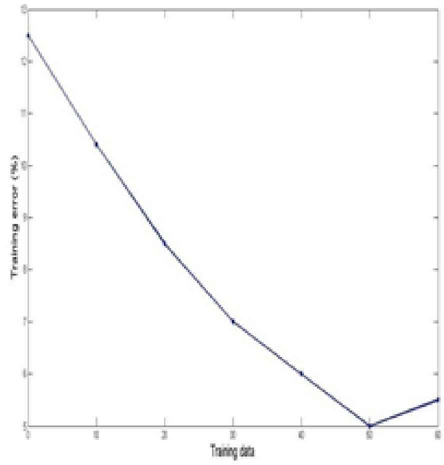

Figure 15: Training error Vs. testing error

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