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An Efficient Ontology Based Machine Learning for Classifying High Definition Satellite Images (Chandrayaan-3)

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ABSTRACT

The analysis of satellite images to determine the kind of land, forest cover, plant type, and other aspects of a particular image has become a standard practice. Object-based image classification for land-cover mapping with remote-sensing data has received a lot of interest in recent years. Several researches have looked into a range of sensors, feature extraction, classifiers, and other important elements throughout the last decade. These data, however, have yet to be gathered into a complete reference on the implications of different guided object-based land-cover categorization methods. To solve this issue, we provide an ontology-based conceptual UKNN classification algorithm in this study. We create an 18-field database from the rit18 database's qualitative and quantitative data in this research. Instead of unexplainable characteristics provided by a CNN, this proposed study uses an ontology-based methodology framework to enable picture classification using features extracted from hyper spectral image data. The image is initially given a Gaussian filter. The suggested UNet K nearest neighbours (UKNN) classifier is utilised to translate the ontology components into image-based parameters, which are then used to improve the classification process. When a typical support vector machine (SVM) is compared to UKNN, we find that UKNN outperforms SVM in classification accuracy.

Introduction

Many organizations have upped their disaster management efforts to save more lives as the frequency of natural and man-made disasters such as earthquakes, tsunamis, forest fires, and floods has grown. For good decision-making, obtaining and combining trustworthy disaster knowledge / analysis in a timely manner is critical. Data from remote sensing and other sources can be integrated to provide useful information, boost relief efforts, and guide damage assessment teams on the ground. Understanding the fundamental problem-solving mechanisms is necessary for developing good image analysis systems. The information given will be more valuable if there is more process knowledge and it can be represented better in the system. [1].

One of the most effective techniques to knowledge representation is ontologies. In past few years, one of the most famous topics of research in geographic information science has been ontologies. Ontologies have been suggested for bridging the semantic gap several times due to their high clarity of information processing, expression, and discovery. Ontologies, either directly or indirectly, describe the content, organization, and essential elements of the simplified worlds that our representations show, as well as the meanings of the terms we use. [2].

The primary goal of this study is to review previous findings in order to obtain a good knowledge of how sensors, land cover types, focused courses, supervised classifiers, geographic areas, categorization techniques, accuracy evaluation methods, and other uncertain variables affect the process and implementation of supervised object-based land-cover image analysis, as well as to develop an effective ontology-based UKNN for classify.

Dataset Description

The RIT-18 dataset was produced to aid in the semantic segmentation of remote sensing images. A DJI-1000 octocopter with a Tetracam Micro-MCA6 multispectral imaging sensor was used to capture the image. 1) Very high resolution multispectral imaging from a drone, 2) six spectral VNIR bands, and 3) 18 item classes (plus background) with a severely uneven class distribution are among the properties of this collection.

Research Gap

Extensive research survey carried out show adoption of ontology and machine learning approach aid in providing efficient and semantic visualization. However very limited work is carried out for extracting ontologies for high-dimensional satellite images. Automatic ontology extraction is a key ideology of many exiting algorithm. To achieve this machine learning technique is adopted. The majority of existing strategies use supervised learning, which means that when a new object is discovered, the model's classification accuracy suffers. To address, here we will develop a semi-automated model for efficient image interpretation visualization using ontology and machine learning technique.

Related work

F. Chaabane*et.al* [3] provides a multi-source and multi-temporal data-driven strategy for detecting and tracking anarchic urban expansion (VHR satellite images and geographic information data). The banned major cities are initially retrieved using a unique SVM-based approach that combines expert knowledge and auxiliary data via ontology building. As a result, expert semantic information and urban design principles, as well as their disagreements with categorization findings, are formalised (typically in the form of phrases). Second, using a novel matrix based on Multi-dimensional histograms Earth Mover's Distance, a framework for comparing spatio-temporal areas is proposed (EMD). A complete definition of a Spatio-Temporal Region (STR) is provided in order to construct the Multi-Temporal Region Matrix (MTRM).

F. Ghazouani*et.al* [4] Concentrate on the topic of semantic scene interpretation for change interpretation. As a result, we've developed a semantic remote-sensing picture scene interpretation technique. The structure for this technique is organised around many layers of interpretation: pixel, visual primitive, object, scene, and change interpretation. Each level has a logical structure for extracting and comprehending important information. Two Landsat scene photos [Landsat Enhanced Thematic Mapper plus (ETM+)] were acquired in 2000 to test the proposed model's importance for semantic scene and change interpretation. and the year 2017 (Landsat 8) Precision, recall, and F-measure metrics were used to demonstrate the recommended methodology's capability for semantic classification.

F. Ghazouani*et.al* [5] the purpose of this research is to explain the characteristics of a spatiotemporal structure from a remote sensing perspective. In this context, the term "dynamic" refers to both processes like decrease and expansion, split and merger, as well as geographical processes like deforestation and urbanisation. To do this, we use description logic, which is a framework for semantic-spatio-temporal reasoning and dynamic representation that has been expanded to the semantic spatio-temporal concrete domain.

S. Kakad*et.al* [6] the expectation maximisation (EM) algorithm and semantic similarity are used to collect, evaluates, and analyses reviews from Amazon and Flipkart, two significant e-commerce platforms. Then, using state-of-the-art models, precision and recall, ontology creation, and execution time are calculated.

D. Eckertz*et.al* [7] produced a machine-readable knowledge base including aggregated and structured knowledge related to AR system configuration There are four types of knowledge that are considered: The framework of the AR system, including its technological and functional components; potential influencing elements; experience and application expertise; and the specifications of individual AR devices The Web Ontology Language (OWL) is used to create the knowledge base, which enables for digitised and partially automated knowledge processing utilising software tools and algorithms.

Corneliu Octavian Dumitru*et.al* [8] demonstrate the creation, implementation, and testing of a complete SAR image analysis system capable of producing semantically defined categorization results (e.g., maps) as well as local and regional analytical insights (e.g., graphical charts).Gabor features are used to generate the initial categorization, and subsequently class designations are determined (labeling). After that, there is an integration process. Expert knowledge can be used into active learning to accomplish this.

Peng Shao*et.al* [9] for mobile trajectory data, this work investigates an ontology-based analysis and semantic query technique. We employ cosine similarity, point-wise mutual information (PMI), and a confined probabilities approach to uncover hidden association and confinement linkages in the data. Then, using taxonomy and comparison methodologies, an ontology-based representation portraying end-user actions is built.

M. Rousi *et al[10]*introduce a conceptual layer to facilitate experience and understanding planning of available information, leveraging ontologies for information processing and conceptual guidelines to find possible farmers noncompliance with the CAP's Greening 1 (crop diversification) and SMR 1 (nitrate-related water pollution) rules. K. Rainey *et al.* [11] describe a dataset that we created to train algorithms for classifying ships in overhead satellite images. Our work revealed a number of problems with datasets and classification algorithms in general, which we explain as a cautionary note to others considering a similar project.

Nandini N [12] explore the different FSP mining algorithms such as SPM, FP growth, and SPADE for extraction of FSPs from WUD of an academic website for a period that varies from weekly to quarterly.

Methodology

Figure 1 depicts the procedure. This methodology heavily relies on ontology. Land cover, picture object attributes, and classifiers all have ontology models. An ontology is a formal, explicit definition of concepts that includes classes (sometimes called concepts), class/concept characteristics (also called roles or attributes), and slot restrictions (facets, sometimes called role restrictions). A knowledge base is made up of ontology and a collection of individual instances of classes. [13]. Initially Rit18 dataset is loaded which is considered as ontology image database (DB).Then the dataset is split into training and testing dataset in the ratio of 70:30. Then both the training and the testing data are passed into the filter to reduce the noise. This work utilizes Gaussian filter to remove the noise. Then the segmentation is proceeding with the UNetwork. The classification is carried with the outcomes of UNet with KNN. To classify the class labels of the satellite image, Grey level co-occur rencematrix(GLCM) based texture features , Gradient magnitude features and then histogram features are extracted for all the bands of rit18 dataset which is considered as a feature vector. The novelty of this research is based on the UKNN algorithm. UKNN algorithm works with the U-net architecture with ResNet as the backbone network. The base model's input form, as well as the custom layer that receives that base mode input and transfers its output to the UNet model, have been constructed. With ReLU activation, the output of the UNet model is passed to further ConvNet layers. The result is then reshaped to 256X256 pixels. The ConvNet layers output is fed to the nearest neighbor algorithm to categories the each region of the satellite image. It improves the classification discriminant's accuracy by using random space ensembles. These space ensembles aid in the efficient use of memory and the handling of missing information. The next process is calculate the distance between the clusters with the features y1,y2,...yk. The test samples are assigned the majority of neighborhood pixels based on the selection of neighbours around the test features. The Minkowski technique is used to calculate the distance function between the clusters.

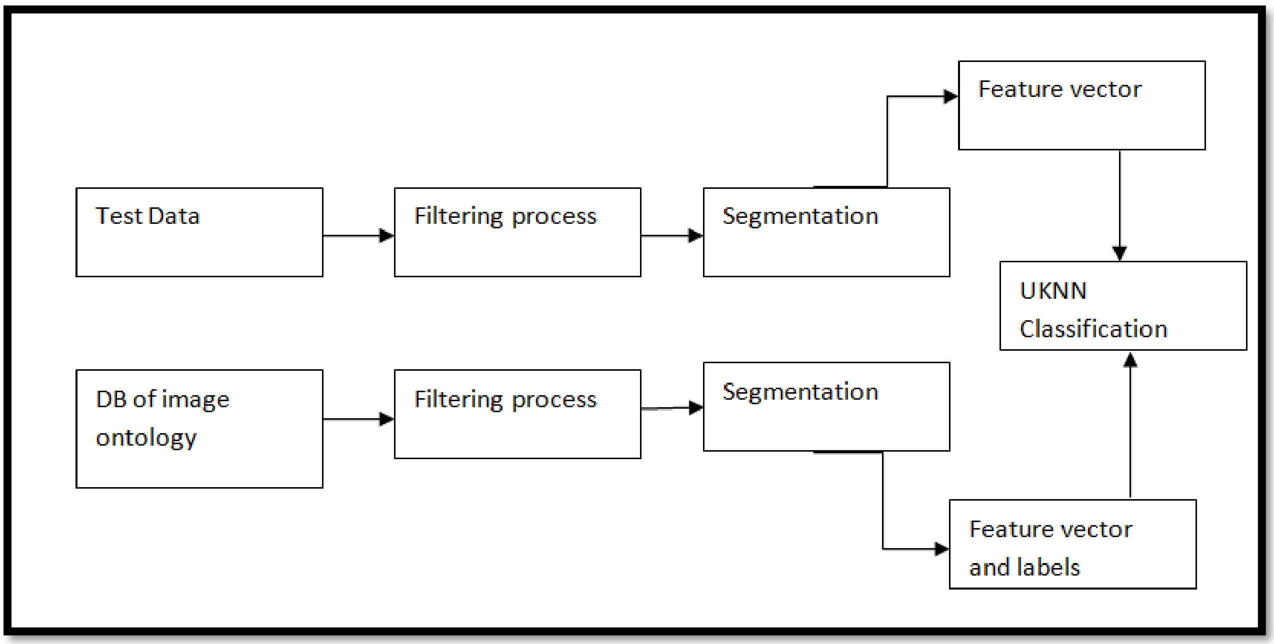

Figure 1. Block diagram of proposed method

Pre-Processing

To increase the image recognition rate, an image pre-processing method using a Gaussian filter is applied. A non-uniform low pass filter is the Gaussian filter. As one advances away from the kernel's centre, the kernel coefficients decrease. The weighting of pixels in the centre is higher than that of pixels on the perimeter. Larger values of generate a broader peak (greater blurring). The kernel size must rise with increasing to maintain the filter's Gaussian character. The Gaussian kernel coefficients determine the value of. At the mask's edge, the coefficients must be near to zero. To sample Gaussian kernel coefficients, the 2D Gaussian function is employed.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \qquad (1)$$

Where σ is the standard deviation of the distribution. The distribution is assumed to have a mean of zero.

Feature extraction

Gradient magnitude

The gradient operator,, is, of course, at the heart of gradient magnitude. The gradient is defined as fc(x,y) in continuous form when applied to a continuous-space image.

$$\nabla f_c(x,y) = \frac{\partial f_c(x,y)}{\partial x} i_x + \frac{\partial f_c(x,y)}{\partial y} i_y \qquad (2)$$

where $\mathbf{i}_x$ and $\mathbf{i}_y$ are the unit vectors in the x and y directions. Notice that the gradient is a vector, having both magnitude and direction. Its magnitude, |∇fc(x0,y0)|, measures the maximum rate of change in the intensity at the location (x_0,y_0). Consider the effect of finding the local extreme of ∇fc(x,y) or the local maxima of

$$|\nabla f_c(x,y)| = \sqrt{\left(\frac{\partial f_c(x,y)}{\partial x}\right)^2 + \left(\frac{\partial f_c(x,y)}{\partial y}\right)^2} \qquad (3)$$

Grey level co-occurrence matrix

The statistical distribution of detected sequences of intensities at defined sites in the image compared to one another is used to create texture attributes in statistical texture classification. Statistics are divided into first-order, second-order, and higher-order statistics based on the number of intensity points (pixels) in each combination. An approach for retrieving second-order statistical texture information is the Gray Level Coocurrence Matrix (GLCM).

The number of grey levels, G, in an image equals the number of rows and columns in a GLCM matrix. The matrice element $P_{ij}|$(x, y) represents how often two pixels separated by a pixel distance (x, y), one with intensity I and the other with intensity 'j', appear in a given neighbourhood. The matrix element $P_{ij}|$ d contains the second order statistical probability values for changes between grey levels I and 'j' at a particular displacement distance d and at a specific angle (). You'll need a lot of temporary data, such as a G matrix for each (x, y) or (d, d) combination when working with a large number of intensity levels G. The GLCMs are particularly sensitive to the size of the texture samples on which they are calculated due to their high dimensionality. As a result, the number of grey levels is typically reduced. The energy and contrast characteristics of GLCM are used in this project. The term "energy" is defined as "the power to turn matter into energy".

$$\text{Energy} = \sum_{\text{i.j}=0}^{\text{N}-1} (P_{ij})\text{^}2 \qquad (4)$$

The contrast feature is defined as

$$\text{Contrast} = \sum_{\text{i.j}=0}^{\text{N}-1} (P_{ij})(i-j)\text{ ^}2 \qquad (5)$$

Where P_{ij}	=	Element *i,j* of the normalized symmetrical GLCM
N	=	Number of gray levels in the image as specified by Number oflevels in under Quantization on the GLCM texture page of the Variable Properties dialog box.

Histogram feature extraction

A discrete function is the histogram of a digital image with grey levels in the range [0, L-1]. An image histogram is a gray-scale value distribution that shows how frequently each gray-level value occurs. The abscissa ranges from 0 to 255 for a 256 8-bit image, and the total number of pixels is 256. The prototype histogram (Image, nbins, min, max, and display) defines the function for this section, where nbins is the number of bins required to build the histogram and min and max are the two values for the histogram's range. The display parameter is a Boolean value that determines whether or not the input image and histogram are displayed. As a vector, the relative frequencies associated with the histogram are returned.

Support vector mechanism (SVM)

The Support Vector Machine (SVM) was invented for linear two-class classification by generating an ideal separation hyper plane with a maximum margin. SVM employs a kernel approach to turn the raw data input into a high-dimensional extracted features, which enhances the classifier's generalization performance when the training data is not linearly separable. We'll go through the fundamental notions of non-linear SVM in this part.

Given training instances (x1, y1), (x2, y2),......, (xm, ym), where xi Rd represents a training example belonging to the class yi + 1,- 1. The SVM converts the original input space into a high-dimensional feature space for training data that isn't linearly separable.utilising a kernel function Mercers' demand might be met by the SVM kernel function. See Gaussian RBF (Radial Basis Function), a popular Kernel approach used in SVM models, for more information. The RBF kernel's value is proportional to the distance between two points. The structure of the Gaussian Kernel is as follows:

$$K(X1, X2) = e^{(-\gamma||X1-X2||^2)} \qquad (6)$$

Where $||X1 - X2|| isaEuclideandistancebetweenX1\ andX2$

The separating hyperplane is defined as

D(x) = w T .x+b (7)

where w is an m-dimension vector, b is a bias term. To obtain the optimal hyperplane, we need to minimize

Q (w, b, ξ) = ½ || w ||2 + C Σ ξ i (8)

Subject to the constraints

Y i (w T xi + b)>= 1 - ξ I for I = 1,…..,m (9)

Where I and xi are nonnegative slack parameters that describe the degree of distortion of the datum. The constant C is a penalty parameter that determines how much of a trade-off between maximum classification rate and lowest training error is acceptable. The soft-margin hyperplane is the resultant hyperplane, where w denotes the soft-margin.

UKNN classification

Segmentation of images Image segmentation's fundamental goal is to appropriately demarcate image objects based on their content. Image segmentation assists in the grouping and then separation of items based on homogeneity criteria. In this paper, UKNN is used to segment and classify images. In a picture, segmentation aids in identifying where objects of various classes are present. Despite slight alterations to the CNN architecture, UNet is a convolutional neural network design that has expanded in size.

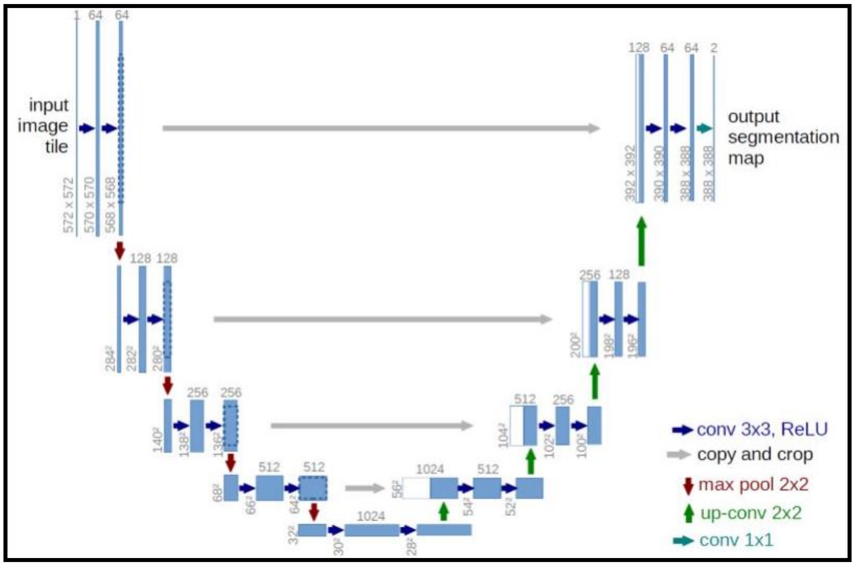

Figure 2. UNet architecture

The suggested solution uses a U-net architecture with ResNet as the backbone network and image net loaded weights as the backbone network. The base model's input form, as well as the custom layer that receives that base mode input and transfers its output to the UNet model, have been constructed. With ReLU activation, the output of the UNet model is passed to further ConvNet layers. The result is then reshaped to 256X256 pixels. Finally, we built a model that receives input (inp) and outputs (outp) from the underlying model (x out). The Unet image is then utilised to perform KNN classification to classify the class labels. It's time to categories the indicated instances that have been assigned. The similarity and reduced dimensionality of the resultant output from the previous phase are the parameters. The K-Nearest Neighboring (KNN) technique is the best appropriate classifier based on the characteristics and efficient Machine Learning algorithms. KNN is based on input data that has been labelled. It deduces the data's functions and produces the appropriate output. It improves the classification discriminant's accuracy by using random space ensembles. These space ensembles aid in the efficient use of memory and the handling of missing information (NaNs).

The KNN classifier is a non-parametric classification algorithm. It does not necessitate any prior understanding of the data structure in the training set. If a new training pattern is introduced to an established set of exercises. It doesn't need to be retrained. The KNN algorithm's output can be thought of as a posterior probability of the input pattern belonging to a specific class. The confidence in prediction improves as the k grows. The training technique is simple, and the sample provides class labels as well as a set of related tuples. For a random number of modules, this approach works. The KNN classification model uses the distance function to map samples to classes.

The KNN Classification technique is used to calculate the distance between the assumed test illustration X and the existing samples y1,y2,...yk. The test samples are assigned the majority of neighborhood lectures based on the selection of neighbours around the test instance. The Minkowski technique is used to calculate the distance function between the samples. When the values are continuous, this approach is used. The number of neighbours considered when allocating a sample X to a class C is proportional to the likelihood of doing so (K).

$$ProbabilityofXtoaclassC = \frac{\sum_{i=1}^{k} distance(c, c(y_i)))}{k} \quad (10)$$

The Euclidean distance is calculated using equation (8)

$$D = sqrt\left(\sum_{i=1}^{n} \left|p_i - q_j\right|^2\right) \quad \mathbf{(11)}$$

Where p is the order of the norm

Pi and qi are pixels

To begin, we organise the explanations and definitions of the objects into semantics using our domain ontology (RDF-triple rules). Second, we describe an encoder method for deconstructing RDF-triple rules using the semantic web rule language, which is based on a multilayer method. The decomposed components of RDF-triple rules are then mapped to the low-level data features provided by optical satellite image and LiDAR height using the deconstructed pieces of RDF-triple rules. Finally, by probabilistically describing the relationships between low-level data features and high-level concepts, a probabilistic belief network (PBN) and a modified TanH function are used to maximise the recognition result. Despite the lack of a training technique based on information samples, the experimental results suggest that our proposed approach is capable of excellent semantic recognition. For complicated urban object recognition, this work proposed multilayer learning algorithms and information graph-based relational reinforcement learning.

Results And Discussion

An experiment is carried out on a subset picture of 28593806 pixels chosen from the rit18 dataset in order to assess the effectiveness of the proposed technique for high resolution remote sensing images object based classification. A process of image pre-processing, such as Gaussian filtering and median filtering, is used to enhance the identification rate of the image. The picture objects are created in the first stage using UNet based segmentation, which is executed in MATLAB 2020a. Image qualities such as texture, form, and pattern have been shown in the literature to aid in the interpretation of high resolution remote sensing images. Second, after segmentation, objects features, which include textural features, are computed. We extract frequently used object features such as gradient magnitude, Histogram features, and GLCM features in this study. The values of all the features rise as the size of the image for which Texture features are selected grows larger. As a result, the best patch size for extraction is 1024x1024 for greater resolution and little data loss.

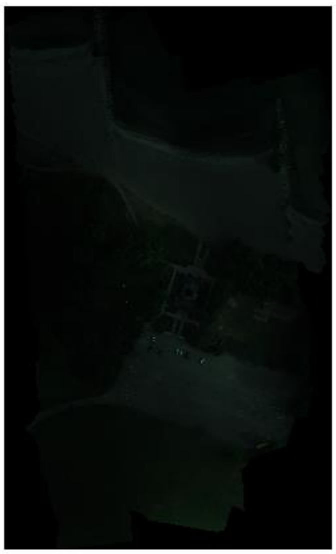

Figure 3. Input image

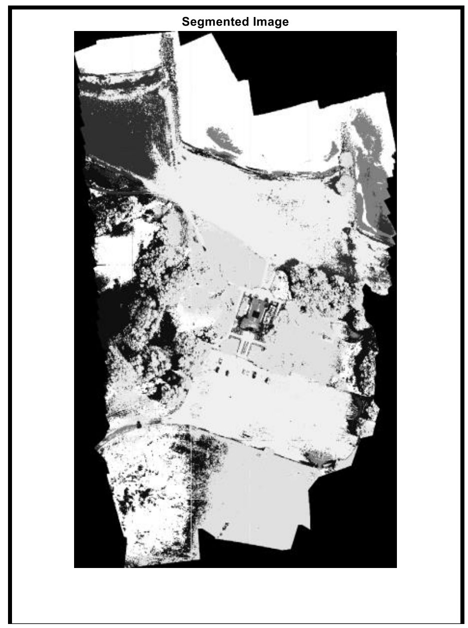

Figure 4. Segmented image

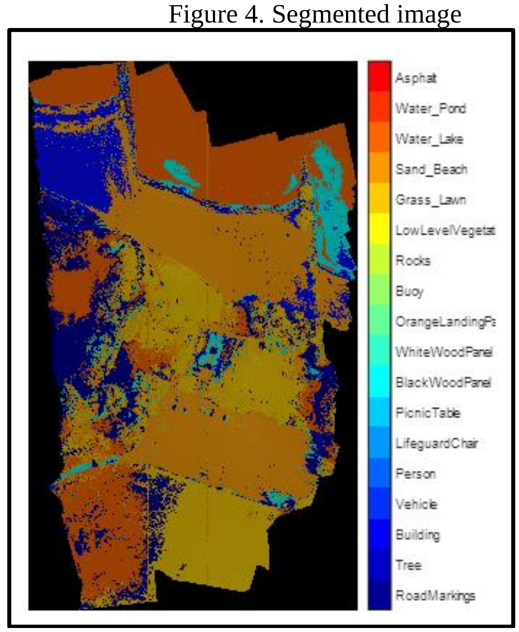

Figure 5. Classified output

This was randomly partitioned into two portions for all bands of the picture objects: 70% of the data was used for training, while the remainder was used to evaluate the efficiency of the suggested UKNN technique. We divided the objects into 18 groups for this study: Road Markings, Tree, Building, Vehicle, Person, Life guard Chair, Picnic Table, Orange Landing Pad, Buoy, Rocks, Low Level Vegetation, Grass Lawn, Sand Beach, Water Lake, WaterPond, Asphalt The segmented image of the provided raw data is shown in Figure 4. The categorised result using the suggested classifier is shown in Figure 5.

Object recognition results

The (peak signal to noise ratio) PSNR value of the original image and the filtered image using the Gaussian filter are shown in Table I. The average values of Sensitivity, Specificity, Error Rate, and Accuracy are shown in Table II (in overall). UKNN has the best Accuracy value, which is 96.58 percent. This is because the specificity value has decreased. In our scenario, however, we believe that a high sensitivity number is more significant than a high specificity value. The error rate obtained also less. Fig 6 shows that the specificity, sensitivity and error rate comparison of SVM and UKNN. It is observed that the UKNN results are superior to SVM. Fig 7 shows that the accuracy comparison of proposed and existing methods.

Table I PSNR Value comparison

Method	PSNR
Before Filtering	23.36
After Filtering	71.53

Table II Performance metrics comparison

Algorithms	Accuracy	Sensitivity	Specificity	Error rate
UKNN	96.58	96.27	57.18	0.0341
SVM	94.89	93.16	57.09	0.051
Decision tree[14]	85.95	-	-	-

Tables II show that the recognition result obtained by our suggested technique outperforms that obtained by a supervised Svm model. To begin with, SVM, such as a supervised lazy classifier, may be difficult to use when dealing with complex variables. The ability of SVM to recognise objects from optical satellite images demonstrates that properties derived from data alone, without human interpretation, are insufficient to identify the item. Despite the fact that SVM does not do well when it comes to applying characteristics for differentiating a range of objects throughout the training phase, it still faces difficulties in conducting faultless recognition without data features. Our proposed method begins by defining the representations of to-be-recognized objects using high-level semantics; it then creates low-level features that correspond to the semantics, making it easier to find low-level features that are more appropriate for the representations of to-be-recognized objects. Our proposed technique can also provide improved recognition results without the need for a training procedure based on data samples.

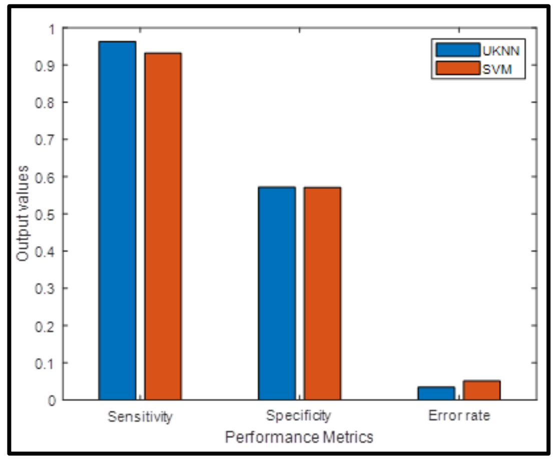

Figure6. Performance comparison

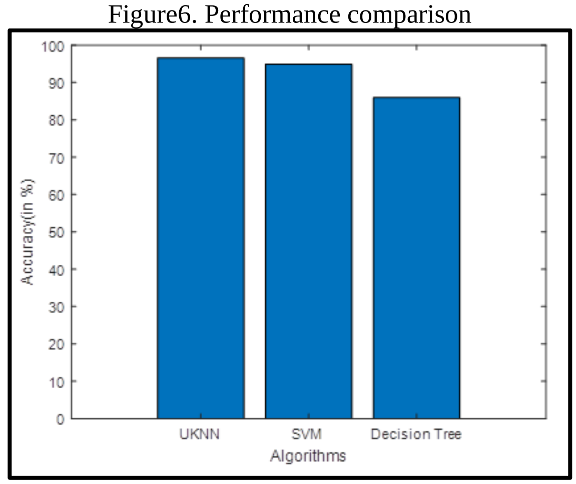

Figure7. Accuracy comparison

By providing more information, the usage of rit18 data can increase classification accuracy and allow us to investigate more ontology levels. Because it is dependent on the initial segmentation process, our approach with ontology yields minimal benefits. This is based on the semantic rules employed in the semantic classification stage, which further confirms the initial classification approach, and certain evident classification flaws may already be fixed inside the semantic classification stage. As demonstrated in Table II, the producer accuracy of our technique is higher for all land-cover types than those based on the decision tree algorithm and SVM. Because the process provides semantic rules to restrict, it tends to decrease misclassification to some level.

Conclusion

By eye site, regions in satellite photos are not always understandable. As a result, satellite image classification is extremely useful for gathering information about a certain location. The process is tough because different classes of photos have similar features and the environment varies. We offer a new knowledge representation and reasoning approach for remote sensing picture interpretation in this study. The method relies on ontology and the UKNN algorithm. SVM and decision tree algorithms are evaluated to the suggested method. Our proposed technique can produce effective recognition with high-level semantics, according to analytical outcomes on the training procedure based on data samples. The UKNN has a precision of 96.58 percent, while the SVM has a precision of 94.89 percent, indicating that the suggested approach outperforms the existing methods. This research contributes to the advancement of complicated urban object detection systems, such as multilayer learning algorithms.

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