VERSATILE UNSUPERVISED MULTI-RESOLUTION CLASSIFICATION METHOD BASED HYDROCARBON EXTRACTION FROM SATELLITE IMAGES

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Abstract: *Satellite image processing is a developing innovation for the oil and gas industry. The look for seafloor hydrocarbon detection is as often as possible an essential block of deep-water investigation programs. On the off chance that thermo genic hydrocarbons are found at the seafloor, investigation hazard can be moderated by the leaks giving proof of a working oil framework. The recuperated leaked hydrocarbons would then be able to be utilized to observe the substance of the subsurface supply and provide pieces of information about their inception. This work intended to enhance the spatial and spectral data of satellite images by detection hydrocarbon in Ramanathapuram district (Tamilnadu state) utilizing Versatile Unsupervised Multi-Resolution modeling classification approach. The proposed Versatile Unsupervised Multi-Resolution based method that automatically classifies the hydrocarbon regions from spatiotemporal remote sensing images. First, a kernel has designed according to the structure of multi-spectral and multi-temporal remote sensing data. Secondly, the Versatile Unsupervised Multi-Resolution framework with fine-tuned parameters has intended for training region samples and learning spatiotemporal discriminative representations. The performance of the proposed hydrocarbon detection method is validated through simulation using the Matlab software. Compared to conventional hydrocarbon extraction methods with a proposed Versatile Unsupervised Multi-Resolution method achieving the best results for accuracy is 97.72%, sensitivity is 98.25 %, and specificity is 94.02%.*

Keywords: *Hyperspectral, Root Mean Square, Correlation Coefficient, Spectral Error, Versatile Unsupervised Multi-Resolution, sensitivity, specificity and accuracy.*

1. Introduction

Nowadays, Earth researchers and investigation geologists consider remote sensing methods an exceptionally helpful instrument for bowl wide evaluation of great zones. Airborne and satellite sensors are viewed as an effective data supplier when coordinated with other investigation devices, for example, seismic, well, gravity and magnetic information. These conditions speak to a genuine test for customary hydrocarbon investigation strategies, while satellite remote sensing can rapidly give data over wide regions at restricted expenses. The hydrocarbon detection study region of sample location map is shows in following Figure.1.

Figure 1. Overview of Study Region

In recent years, some remote sensing methods development rapidly such as the lasing fluorescence remote sensing, the synthetic aperture radar (SAR), thermal infrared remote sensing. The above remote sensing methods have already played more and more vital roles in the off-shore oil pollution examination, but there are some certain limitations. Hyper spectral sensors are collect information as a set of transparent images say the band. These bands represent a narrow wavelength range of the electromagnetic spectrum named as a spectral band. It usually contains hundreds of spectral bands over a wide range typically at least 0.4 to 2.4 micrometer as visible through middle infrared ranges. At present progress is towards understanding the relationship between oil and gas leakages from pipelines and natural wells and their effects on the vegetation and spectral signature.

2. Research Background

Various image segmentation and classification methodologies have been discussed for satellite image processing for hydrocarbon detection and to consider few of them here.

The quick improvement of present day remote sensor innovations has given a lot of data about the earth's surface, encouraging an extensive variety of remote sensing applications [1-2]. There are immense measures of remote sensing information around the world either open or private. This makes an enormous test to comprehend

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this information quickly for their generation [3]. Hydrocarbon microbial oxidation at first glance landscape deliver Carbon dioxide (CO_2), Sulphuric corrosive (H_2S) and other natural acids [4] which change illicit specks of dirt into Caroline. For instance, in [5-6] recommended the utilization of Landsat multispectral information to feature Caroline-rich territories. At the point when microbial movement happens on Ferric oxide (Fe_2O_3) rich areas, the outcome is a decrease from ferric to ferrous oxide which delivers the chromatic modification known as dying of reed beds and a marvel that can be distinguished through the examination of the intelligent spectral bands [7].

A few kinds of image classification strategies were investigated in the previous decade to sensing the hydrocarbon from satellite images. A portion of the prominent strategies are K-Nearest neighbor (KNN) classifier [8], Support Vector Machine (SVM) classifier [9] and Maximum Likelihood (ML) classifier [10]. The exactness of classification is additionally enhanced by considering the advantages of various classifiers and joining them to frame a classifier that have every one of the benefits of various classifiers. This sort of joining diverse classifiers is called gathering strategy. In group strategy, clustering and classification process can be consolidated [11-12].

In the recent past new scope of computational algorithms known as Swarm Intelligence Algorithms, which are motivated from the conduct of social bugs, have picked up the consideration of scientists for classification of remotely detected information [13-15]. Two broadly utilized swarm insight algorithms are Ant Colony Optimization (ACO) [16] and Particle Swarm Optimization (PSO) [17]. Hybrid approaches utilizing these two and other effectively existing strategies are being explored different avenues regarding right now [18]. Self-Organizing Ant Algorithm [19] is one such mixture algorithm which consolidates the ideas of Kohonen Self sorting out component outline and Ant Algorithm [21]. A modified version of this algorithm is used in this work for the satellite image classification for hydrocarbon detection.

3. Materials and Method

The objective of the proposed system is to detect the hydrocarbon form satellite image and to increase the computational speed, accuracy and reduce the computational dimensionality using soft computing methods. The proposed system will extract the oil and gas Extractions of hydrocarbon from the hyperspectral image, the block diagram of the proposed hydrocarbon detection from satellite image is shown in Figure.2. The proposed system comprises of four stages like pre-processing, segmentation, Hydrocarbon Feature Extraction and classification. First, the input image is pre-processed followed by segmentation is applied.

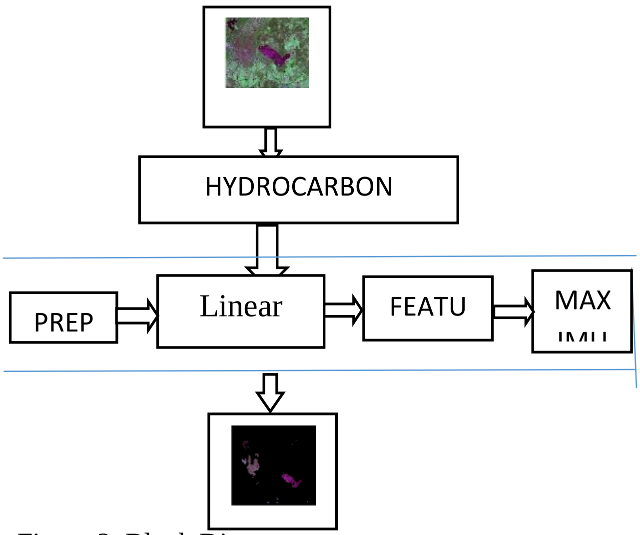


Figure 2. Block Diagram

After segmenting and clustering the satellite images based on the color reflectance, the proposed system extracts the Hydrocarbon Feature Extractions embedded in the satellite images. Versatile Unsupervised multi-resolution classifier models are built to recognize the type of objects in the satellite images. Using the Versatile Unsupervised multi-resolution classifier technique, different ensemble models from the seven vector sets are generated and evaluated for obtaining the performance metrics of hydrocarbon. The proposed Versatile Unsupervised multi-resolution classifier uses the hold-out method for splitting the dataset into training and testing samples.

3.1 Pre-processing - Resourceful ethical filter

Preprocessing of satellite images before image application is essential. Preprocessing commonly encompasses a series of sequential operations, such as atmospheric correction, image registration, geometric correction, radiometric correction and masking of a distorted raw image. The motivation of these corrections in preprocessing is to make images distortion free for further usability. In image registration, spatially alignment of two or more scenes obtained at the different time or from various sensors. The image registration is used in different kinds of literature as geometric registration and rectification of geometric distortion or polynomial affine transformation. The image acquired earlier date is known as a base image and, recently received the image with error is to be corrected. Figure.3 shows the complete methodology for implementation of preprocessing algorithms and Figure.4 shows the preprocessed result of input image.

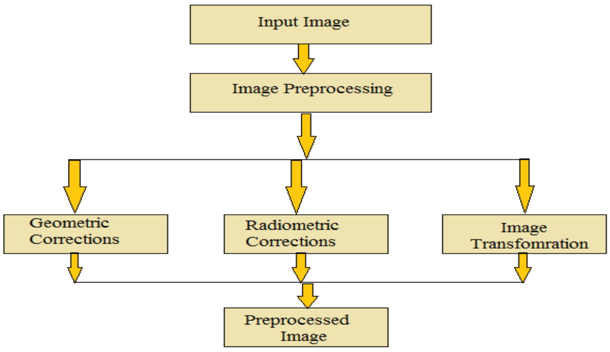
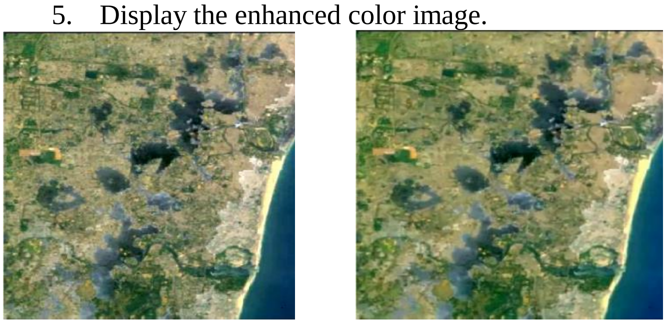


Figure 3. Flowchart of Preprocessing

3.1.1 Resourceful Ethical Filter Algorithm

1. Load the image from data set.
2. Initializethe pixel range ω=3for each image.
3. Compute the minimum, median and maximum of the pixel values s_(i,j)^(min,w), 〖s〗_(i,j)^(med ω) ands_(i,j)^(max ω)froms_(i,j)^ω.
4. Also convert a separate composite file into individual hue (H), saturation(s) and value (v) components adaptively based on the adaptive median filter.
5. Display the enhanced color image.



4a) Input Image 4b) Preprocessed Image

Figure 4. Preprocessing Result

3.2. Unsupervised Multi-Scale Invariant Clustering Segmentation

The algorithm of unsupervised multi scale invariant clustering segmentation has a place with the general class of district developing sort of segmentation plot. The region that is identified for segmentation ought to be closed. Area based segmentation is likewise named as Similarity-Based Segmentation. The limits, typical area and influenced district are recognized for segmentation. In every single step somewhere around one pixel is identified with the region is taken into consideration. It is the multi resolution unsupervised segmentation method of examples got from observations, information things and additionally include vectors into groups or clusters. To complete clustering exercise, the numerous segments of a commonplace clustering errand have been considered, which incorporate the example portrayal, meaning of example closeness measure proper to specific information area and clustering. The accompanying condition is utilized to gauge the clustering separation.

$$\delta_i = \begin{cases} & min_j^{dij} P_j > P_i \\ min_j^{dij} & P_j \text{ is the highest density} \end{cases}$$

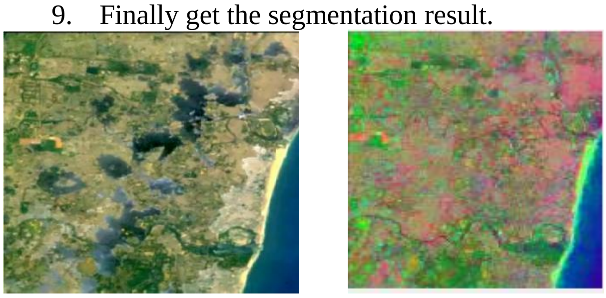
Together with the description of projecting the input image into color spaces and the basic idea of MSIC segmentation algorithm, the novel segmentation approach could be described as follows:

1. Transforming the information image into a Hydro-Carbon Feature Extraction portrayal.
2. Read the principal image data to get the depiction in six cluster channels
3. Recognizing the every cluster centers and number.
4. Conferring to the guidelines exhibited previously, picking the information focuses with high thickness (ρ) and impressive separation (δ) as the cluster focuses.
5. conveying the clusters and Printing the point x_i with a similar mark of point x_i , it was satisfying the following two circumstances:

$$P_i > P_j$$

$$d_{ij} = min_{i\#1}^{d_{ij}}$$

6. The Euclidean value was calculated for every cluster.
7. If that the Euclidean value was not nearest to cluster means move it into the another closest cluster.
8. Repeat the all steps until the point that a whole experience each one of the data focuses achieves no data demonstrate moving from one cluster another.
9. Finally get the segmentation result.



a) Preprocessed Image 4b) Segmentation Image

Figure 5. Clustering Segmentation Results

The multi scale invariant clustering segmentation's result is appeared in Fig.5. In this research work totally six types of clusters was consider to detect the hydrocarbon content from input image. By using multi scale invariant clustering segmentation to correctly identify the hydrocarbon regions.

3.3. Hydrocarbon Feature Extraction

The efficiency of Hydrocarbon include is needy on the algorithm as well as on the shading space picked. In this area to talk about how the Hydrocarbon features are extracted from satellite images. From the analysis to found that pairwise mix of surface descriptors outputted great

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outcomes. Including more descriptors, be that as it may, did not enhance the outcomes significantly but rather would initiate a higher computational load. The hydrocarbon feature extraction algorithm steps are discussed in section 3.3.1. Among various descriptors utilized, the difference measure gave excellent separation control. In any case, the best outcome was acquired when difference and entropy measure were joined for segmentation. The consolidation of the entropy measure can conquer the missing data identified by differentiation measurement alone.

3.3.1. Hydrocarbon Feature Extraction Algorithm

Input: Unsupervised Multi-Scale Invariant Clustering Segmentation

Output: Extracted Hydrocarbon Feature Extraction Vectors

Process:

Step 1: Remove the noise from image using resourceful ethical filter

Step 2: Assign Hydrocarbon Feature Extraction Values Fv

1. Fix the Diameter = Minimum Diameter of Fv_0;
2. Fix Hydrocarbon Feature Extraction Parameter F_in= Diameter *0.31

Step 3: Estimation of the Vector Hydrocarbon Feature Extractions

1. Fix V_1 = An (Fv_0, F_{in})
2. Fix V_2 = Fv_0 – V_1;

Step 4: For All Segmented Hydrocarbon Feature Extraction Values Fv

1. Fix the Hydrocarbon Feature Extraction Parameter F_out = 1.81*sin

Step 5: Estimation of the Vector Hydrocarbon Feature Extractions

Step 6: Construct spectral Zone Hydrocarbon Feature Extraction Vector values

SZFv = $\int_{j=1}^{k} (V\_1 \cap V\_2 \cap V\_3) \in Ds(j)$

Stop.

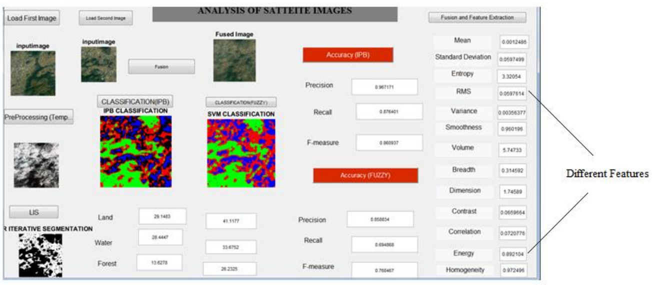

Figure 6.GUI Screen with Hydrocarbon Feature Extraction

The above Figure.6 shows the Hydrocarbon Feature Extraction output results of a GUI screen with Hydrocarbon Feature Extraction using Hydrocarbon feature extraction method.

3.3.1. Peak Signal to Noise Ratio

Peak Signal to Noise Ratio (PSNR) is used to evaluate the noise between input and output image. Based on the PSNR value the image quality was analyzed.

$$PSNR\ (dB) = 20\ log \frac{255\sqrt{3MN}}{\sqrt{\sum_{i=1}^{M}\sum_{j=1}^{N}(B'(i,j) - (B'(i,j)^2)}}$$

Where

B = Input Image

B' = Output Image

i = Index Value of pixel in row

M = Index Value of pixel in row

N = row and column numbers

3.3.3. Root Mean Square Error

The RMSE is another standard measure of a difference between the reference image and the output image given by:

$$RMSE = (\sum_{i=1}^{M}\sum_{j=1}^{N}[I_R(i,j) - I_F(i,j)])^{1/2}$$

Where,

$I_R(i,j)$ = Pixel values of the reference image.

$I_F(i,j)$ = Pixel Value of fused image respectively.

3.4. Versatile Unsupervised Multi Resolution Classification

The Versatile unsupervised Multi resolution algorithm is a speculation of the slightest mean square algorithm that alters network weights to limit the mean squared blunder between the coveted and genuine outputs of the network. The Versatile unsupervised Multi resolution algorithm prepares a given feed forward multilayer network for a given arrangement of info designs with known classifications. At the point when every passage of the example set is displayed to the system, the system looks at its output reaction to the example input design. The output reaction is then contrasted with the known and wanted output, and the mistake esteem is ascertained. Given the blunder, the association weights are balanced.

1. Take an input satellite image from study region.
2. Make Preprocessing utilizing Resourceful Ethical Filter.
3. Segmentation utilizing Multi-Scale Invariant Clustering Segmentation.
4. Concentrate the Vector Zone Hydrocarbon Feature Extraction.
5. Gathering the comparable components.
6. Apply the proposed classification to remove the Hydrocarbon region from segmented image.
   a. Discover the Posterior Probability (PP) for each pixel.
   b. Find out the threshold ranges for every pixel in classified regions.
7. If (PP≥T (threshold Value))
   a. To classify every pixel to associate the parts and to consolidate the areas.

   Else

   Classify the inside pixels.

End if

8. Run continuously from step 6 to step 8.

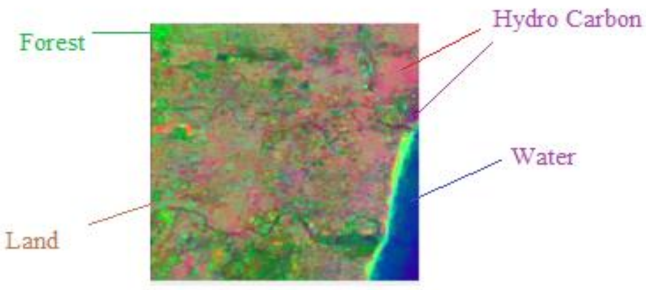

Figure.7: Versatile Unsupervised Multi resolution – Classified result

The proposed versatile unsupervised Multi resolution based classification result was shows in above Figure.7. In this work, the Quality estimations were created by taking a gander at the removed Hydrocarbon Feature Extractions against an exact reference set put away by a visual comprehension of the LANDSAT test image. The accompanying section is utilized to assess the execution of the proposed classification algorithm.

Table 1
Comparison of fault detection time

Types of fault	Fault detection time in ms	
	WSE Method	**dqWSE method**
Single line to ground	6	4
Double line to ground	7	4
Symmetrical fault	8	4

4. Results and Discussion

In this exploration work have utilized a versatile unsupervised Multi resolution Algorithm for Classification of Hydrocarbon from remotely detected information and recommended another fortification factor for the pheromone updation. A simulation results of algorithm is led by arranging a high resolution, multi-spectral satellite image of Ramanathapuram region.

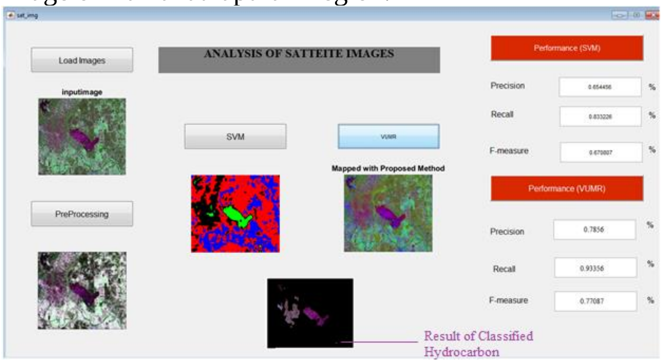

Figure.8. Simulation GUI screen

The simulation of the proposed hydrocarbon extraction system was evaluated using matlab Simulink software using versatile unsupervised multi resolution approach. The Graphical user Interface (GUI) screen of the proposed system is shows in Figure.8.

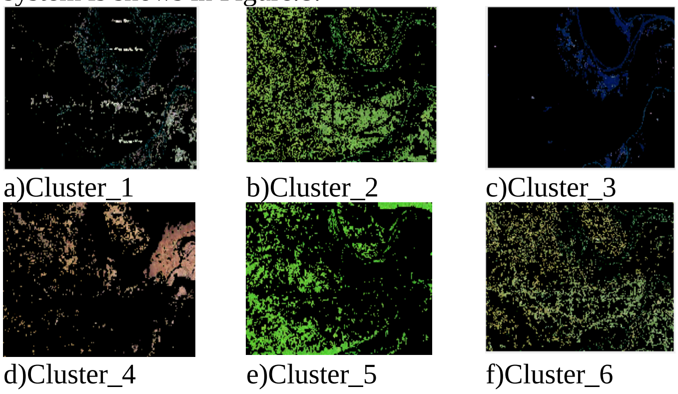

Figure.9. Hydrocarbon Detection Segmentation results of the first image

The segmentation results of hydrocarbon detection LANDSAT's first image is shows in Figure.9. In figure 9c and 9d shows the Hydrocarbon Regions. The same Procedure repeated for the second input and as the number of clusters increases leading to better accuracy in the segmentation results.

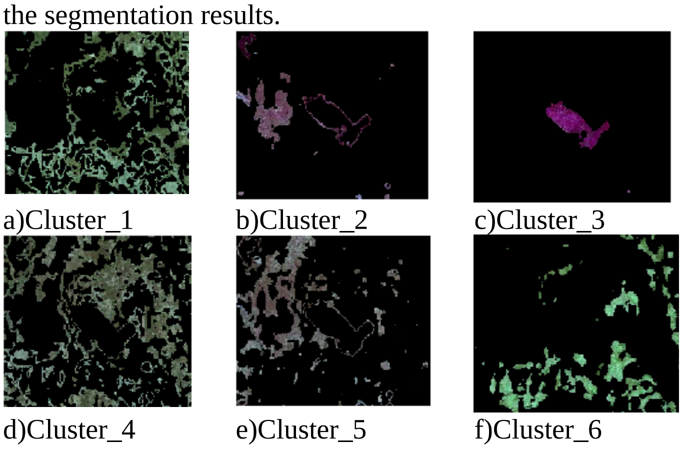

Figure.10: Clustering segmentation Result for Hydrocarbon Detection

The segmentation results of hydrocarbon detection LANDSAT's first image is shows in Figure.10. In figure 10b and 10c shows the Hydrocarbon Regions. The same Procedure repeated for the second input and as the number of clusters increases leading to better accuracy in the segmentation results.

Table 1
Performance Comparison for Proposed and Existing Method

Metho	**Hydroca rbon Tracking**	**Hydroca rbon Tracking**	**Hydroca rbon Tracking**	**Time Comple xity**

ds	Sensitivity (%)	Specificity (%)	Accuracy (%)	(sec)
Versatile Unsupervised Multi-Resolution (VUMR)	94.02	98.25	97.72	5.01
Maximum like hood classification	93.27	92.	94.12	7.95
SVM	89.45	90	90.74	12.30

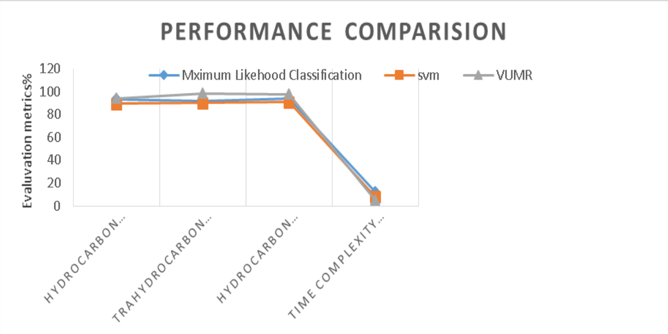

Figure.10: Performance Comparison for Proposed and Existing Method

The performance comparison of hydrocarbon detection for satellite images in proposed and existing classification methods was demonstrates in Figure.10 and Table.1. As compared with existing maximum like hood classification and SVM methods the proposed versatile unsupervised multi resolution classification strategy was give perfect results of sensitivity, specificity and accuracy.

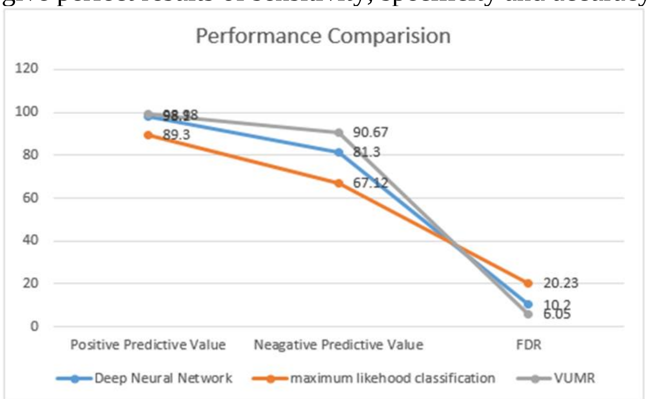

Figure.11: Graphical representation of different evaluation metrics

The above Figure.11 shows the evaluation metrics of proposed system like positive predictive value, negative predictive value and false detection rate values are compared with traditional methods like deep neural network and Maximum like hood classification. As compared with existing methods the proposed versatile unsupervised multi resolution method give the better result.

Table 2

Precision, F-Measure and Recall analysis

Methods	Precision (%)	Recall (%)	F measure (%)
VUMR	87.65	90.45	5.65
Maximum like hood classification	76.1	88.5	10.56
K –means clustering	72.1	87.1	20.23

Table 2 demonstrates the F- measure, recall, and precision come about utilizing the different element spaces. The accuracy of different Hydrocarbon Feature Extractions is extraordinarily identical in real time situation. The experimental results has been justify that the essential point here has been the preparing time, which hasdocumented to histogram includes as it is insignificant complex than other conventional methods.

4. Conclusion

In this work utilize versatile unsupervised Multi-Resolution Classification strategy for Hydrocarbon identification in Ramanathapuram district using satellite image application. The input image is preprocessed and removes the Hydrocarbon Feature like gray esteem and unknown gray distribution. The proposed Versatile Unsupervised Multi-Resolution based method that automatically classifies the hydrocarbon regions from spatiotemporal remote sensing images. First, a kernel has designed according to the structure of multi-spectral and multi-temporal remote sensing data. Secondly, the Versatile Unsupervised Multi-Resolution framework with fine-tuned parameters has intended for training region samples and learning spatiotemporal discriminative representation.The proposed technique has produced useful results in image classification to improve the hydrocarbon feature detection accuracy and reduces the false classification ratio. The work achieve the result of classification accuracy of Hydrocarbon detection is 97.72%, sensitivity is 98.25 % and specificity is 94.02%, which is far better than earlier results in this exciting area of research. The presentation of the execution is examined, a comparison is also made regarding the hydrocarbon detection accuracy and clustering accuracy, time complexity, and false classification ratio are presented.

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