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Optimal Radial Basis Neural Network (ORB-NN) For Effective Classification of Clouds in Satellite Images with Features

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Abstract

Automatic cloud detection and classification utilizing satellite cloud imagery have different meteorological applications, for instance, weather forecasting and climate monitoring. Satellite perception is vulnerable to noises, as conventional cloud classification strategies are sensitive to noises and exceptions; it is durable for traditional cloud classification techniques to accomplish solid outcomes. To manage these issues, a satellite cloud classification strategy utilizing Optimal Radial Basis Neural Network (ORB-NN) based machine learning classifier is utilized. This proposed technique includes three primary stages preprocessing, feature extraction (wavelet and texture) and classifier.Here RB kernel optimization process optimizes inspired optimization model i.e. Genetic-based Harmony Search (GHSO) optimization are used to enhance classification performance of cloud images. In the testing process,the input cloud imagesare classifiedas low level, medium level and High level with most extreme accuracy contrasted with existing papers. The performance of the outlined ORB-NN classifier is assessed and which gives the general accuracy of 97.37 % with 95.66% for Low-Level Clouds, 98.77% for Middle-level Clouds and 93.33% for High-Level Clouds compared to different classifiers.

Keywords: Satellite image, Feature extraction, Image classification, NeuralNetwork, radial basis function, and optimization.

1. Introduction

Clouds play an essential part in the Earth structure. They essentially influence the heat expenses arrangement by reflecting short-wave radiation, engrossing and emanating long-wave radiation [1]. Satellite cloud imagery has turned out to be one of the crucial means for weather forecasting and climate investigation [2]. Cloud classification through satellite images is an approach of essential significance in numerous climatic and ecological examinations, for example, weather investigation and estimating [3]. Certainly, cloud classification from satellite sensor data must be performed consequently, in consequence of the amount of information to be prepared, and to ensure objectivity in the classification [4]. The vast majority of the texture-based cloud classification strategies in the early research utilized factual measures in view of Gray Level Co-Occurrence Matrix (GLCM) [5]. Initially, this approach decreases inside class spectral variety and usually evacuates the purported salt-and-pepper impacts that are usual in pixel-based classification [6]. Cloud classification techniques can generally be separated into following classes: the threshold approach, conventional statistical strategies, and new strategies, for example, Artificial Neural Network (ANN) [7]. Consequently, a precise and cost-powerful strategy for cloud detection and classification in view of satellite images has been an awesome enthusiasm of numerous researchers [8]. Generally, because of anassorted variety of cloud flow and complexity of basic surface [9], it is normal to discover that single Infrared channel data could not adequately recognize cloud sorts in light of the fact that diverse cloud sorts may have comparable cloud-top brilliance temperatures (Tbb) [10].With a specific end goal to classify distinctive cloud types adequately, the gray estimations of every pixel in the cloud images from five channels are chosen as fundamental features [11]. The drawbacks of this strategy are that it can't portray the image contents, for example, cloud shape and furthermore prompts the inconvenience in recovering images [12]. Obviously, cloud classification from satellite sensor data must be executed naturally, owing to the amount of data to be prepared, and in addition to ensuring objectivity in the classification [13].Therefore, very effective and powerful cloud classification plans are required for programmed handling of satellite cloud imagery for climatological applications [14].

2. Literature Review

In 2017 Akansha Singh and Krishna Kant Singh [15] have proposed the RBFNN has learning capacity and can suitably respond to inconspicuous data. This settles on the system a decent decision for satellite images. The effectiveness of RBFNN is extraordinarily affected by the learning algorithm and seed point choice. Along these lines, in this paper ghostly lists are utilized for seed choice and GA is utilized to train the system. The proposed technique was utilized to characterize the Landsat 8 OLI images of Dongting Lake in South China. The execution of the proposed technique was examined and compared with three existing strategies and the error matrix was computed to test the execution of the strategy.

In 2016 Teng Wu et al. [16] mechanized cloud detection by presenting an image coordinating based strategy under a stereo vision structure, and the optimization utilization of non-cloudy regions in stereo coordinating and the era of Digital Surface Models (DSMs). This procedure consists of the accompanying strides: an image based DSM is right off the strike produced through a various primitive multi-image matcher. When it is lined up with the reference DEM in light of common features, places with huge tallness contrasts between the DSM and the DEM will recommend the potential cloud covers. Distinguishing cloud at these spots in the images at that point empowers exact cloud depiction. The cloud detection accuracy for images lacking snow is as high as 95%. Exploratory outcomes exhibited that the proposed technique can altogether enhance the utilization of the cloudy panchromatic satellite images for territory extraction.

The application of Bayesian network classifiers to cloud classification in satellite images are analyzed by J. Alonso-Montesinos et al in 2016. [17] There is a need to decrease the effect of customary power generation requires an expansion in the optimization of option frameworks that create less natural contamination. This adjustment benefits plant execution and enables power administration to be incorporated into the power framework. In any case, the dominant part of cloud examines decide air parameters, which are some of the time not accessible. In this work, they have built up a programmed, completely exportable cloud classification model, where Bayesian system classifiers were connected to satellite images to decide the nearness of clouds, grouping the sky as cloudless or with high, medium and low cloud nearness. There was a normal achievement likelihood of 90% for all sky conditions.

In 2016 Wei Jin et al.[18] Satellite perception was defenseless to noises, while customary cloud classification strategies were delicate to noises and exceptions; it was hard for conventional cloud classification techniques to accomplish dependable outcomes. To manage these issues, a satellite cloud classification strategy utilizing Adaptive Fuzzy Sparse Representation Based Classification (AFSRC) was projected. Initially, by characterizing adaptive parameters identified with weakening rate and basic participation, an enhanced Fuzzy enrollment was acquainted withhold the fuzziness and vulnerability of satellite cloud imagery; secondly, by powerful combination of the enhanced Fuzzy enrollment work and Sparse Representation-Based Classification (SRC), particles in preparing word reference were upgraded; at last, a versatile Fuzzy sparse portrayal classifier for cloud classification was proposed.

In 2015 Yi Yuan and Xiangyun Hu [19] had demonstrated that an image was first sectioned into superpixels with the goal that the descriptor of every superpixel can be calculated to shape a feature vector for classification. The support vector machine algorithm is then connected to segregate cloud and nonblood locales. From there on, the Grab Cut algorithm was utilized to remove more precise cloud locales. The key to the strategy was to manage the profoundly fluctuating examples of clouds.

The bag-of-words (BOW) modelwas utilized to construct the compact feature vectors from thickly removed nearby features, for example, thick Scale-Invariant Feature Transform (SIFT). The algorithm was tried by utilizing 101 Rapid Eye and 86 Landsat images with many cloud designs. These images accomplished 89.2% of accuracy, 87.8% of review for Rapid Eye, 85.8% of exactness, and 83.9% of review for Landsat.

In 2013 Jules R. Dim and TamioTakamura [20] have proposed a preferred way to deal with the frequently utilized cloud optical and thermodynamic properties based classifications. This approach depends on the utilization of edge detection methods on Cloud Top Temperature (CTT) got from worldwide satellite maps. The angle outline through these methods is then used to recognize different sorts of clouds. The edge detection procedures utilized depend on the possibility that a pixel's neighborhood contains data about its force.High slope ranges would correspond to cumulus-like clouds, while low inclination regions would be related with stratus-like clouds. Following the use of these standards, the aftereffects of the cloud classification acquired were assessed against a common cloud classification strategy in light of cloud optical properties' varieties. Generally, great matches between the two methodologies were acquired.

3. Problem Identification

- In late decades, different classifier strategies were produced to classify the cloud satellite imagery utilizing remote detecting standards and image processing procedures.
- It couldn't care less with cloud removal preprocessing operation which is as yet done physically. Clouds and shadows were combined by utilizing a Markov random field to recognize clouds [10].
- In some classifier like KNN, SVM happening in the investigation of arbitrary data is the incorrect class task because of theconcurrent appearance of more than one predefined cloud class [14, 19]. Despite that, some classification issues contain more than two classes. So by combining a huge number of twofold classifiers multi-class classifies can be acquired.
- The first disservice is that the Bayesian classifier makes an extremely solid suspicion on the state of your data dispersion, i.e. any two features are free given the output class [17].
- Machine learning on a regular basis can be effectively connected to these issues, enhancing the proficiency of frameworks and the designs of machines. In existing satellite image classification SVM were considered. To do a multi-class classification, pairwise classifications can be utilized.

- The issue in fundamental NN model as do not function admirably when there are a large number or a great many input features and hard to comprehend the model [15, 10]. In existing written works unfit to show signs of improvement classification rate and accuracy of existing classifier for cloud satellite image process.

4. Methodology

In recent years, extensive research has been centered on the cloud classification area. A decent audit of the accessible plans is given in existing literary works. This area depicts the overall methodology (Figure 1) of the software system created and the test conducted to classify various types of clouds in satellite images in view of Machine Learning (ML) approach. At first satellite database images to preprocessing steps and two principle phases of cloud detection process as feature extraction and classifier model. This feature extraction model, extraction the cloud data's in images texture and wavelet features are considered, this wavelet feature broadly utilized as a part of processing strategy for object detection and classification. Wavelets have been associated in the precedent to inspect images.Textural features are those qualities, for example, smoothness, fineness, and coarseness or certain pattern related with an image. Lastly, ML supervised classifier as Neural Network (NN) is used to cloud satellite classification process. For proficient classification process, optimal Radial Basis (RB) function is utilized as a part of default NN structure. Henceforth, training and testing dataset have been made regarding the issue of waterbody extraction by the space master. The testing dataset and the weight file has been fed as input to optimal RBF output which is then compared with actual output in thetesting dataset to compute the testing accuracy.

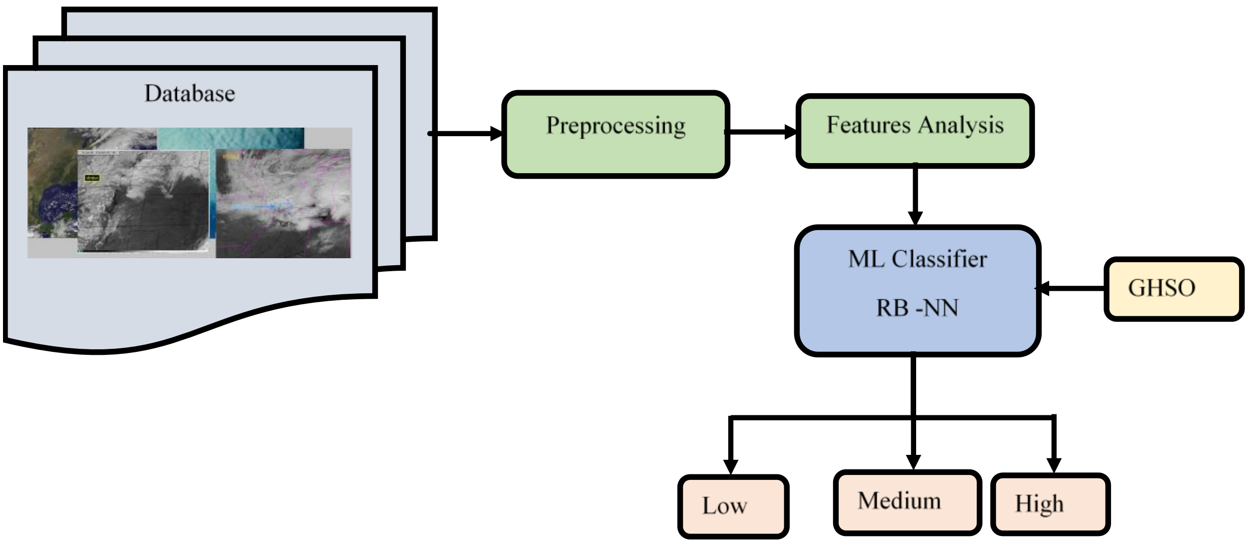


Fig 1: Block Diagram for Proposed Model

This proposed model consists of three plans to classify cloud satellite images demonstrated as follows.

- Pre-processing
- Feature Extraction
- Classifier Model

4.1 Preprocessing Scheme

The median filter is utilized to enhance the adaptability of the filter to change its size as requirements are established in the form of nearby noisedensity. Each output pixel contains the median value in the 3-by-3 neighborhood around the corresponding pixel in the input images. The edges of the images nonetheless are supplanted by zeros. On the off chance that image is uproarious and target pixels neighboring pixel worth is someplace around 0's and 255'swhen we supplant pixel respect with the center regard.

4.2 Feature extraction scheme for cloud classification

Feature extraction is a vital stage for any pattern recognition task particularly for cloud classification since clouds are remarkably variable and it is hard to discover dependable and strong features. These features are to sort the image pixels to various cloud types. Low-level feature extraction includes programmed extraction of features from an image. Here two Different features are considered which are

- Wavelet Features (Discrete Wavelet Transform)
- Texture Features (Grey Level Co-occurrence Matrix)

By and large, these features are figured after an image has been classified. The shadow data is the most troublesome one for investigation and has not been completely misused.

(a) Discrete Wavelet Transform (DWT)

Wavelet transform offers a system in which a signal is rotted, with each level identified with a coarser determination or lower frequency band, and higher frequency bands. Two most vital gatherings of transforms are there, continuous and discrete. In DWT, which applies a two-channel filter bank (with downsampling) iteratively to the low-pass band (at first the first image).

- In the wavelet transform the feature extractions are done by methods for the two phases appeared as takes after:
- Contingent upon particular frequency sub-bands the regular images are decaying.

- The broke down images at unmistakable frequency sub-bands are assessed utilizing various resolutions.
- For the input image, $i(t)$ the wavelet transform is given as

$$W(x,y)=\int_{-\infty}^{\infty} i(t).\psi x,y(t)dt \quad (1)$$

Where $\psi x,y(t)\rightarrow$ wavelet function.

The consequential beat image from the Low pass filter downsampledby 2 yields the coarse coefficients and the subsequent image from the high-pass filter aredownsampledto produce the detail coefficients, which are delineated in Figure 2.

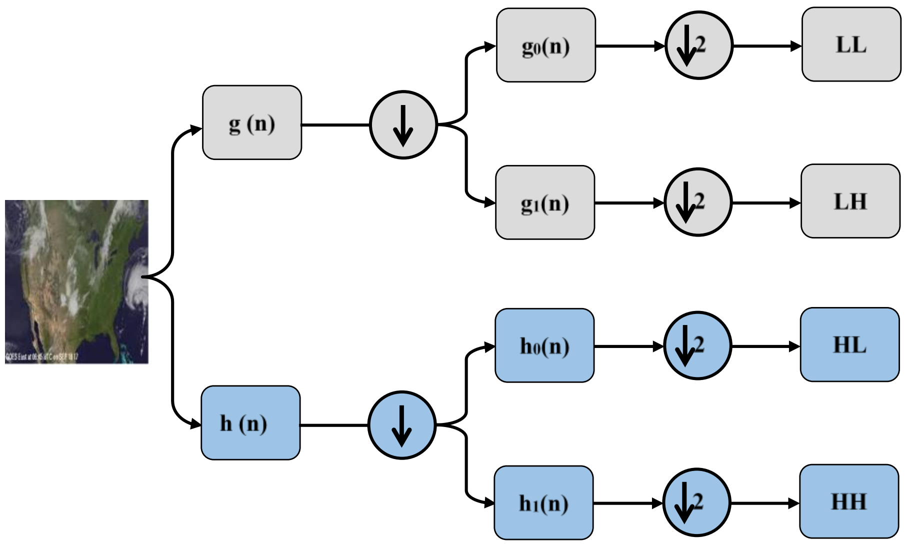


Fig 2: DWT

Hand L denotes high and low-pass filters respectively, ↓2 denotes subsampling.

Each stage has both horizontal (H) and vertical (V) detail coefficients. As specified before there are statistical variables related at each level and for both horizontal and vertical coefficients. In this work, the images are changed into their particular coefficients that detach the vertical, horizontal and diagonal sub-groups.

(b) Texture Features

In statistical texture analysis, texture features are calculated from the statistical circulation of watched combinations of intensities at indicated positions with respect to each other in the image. The Gray Level Co-occurrence Matrix (GLCM) technique is a method for separating second order statistical texture features considered for our proposed model.

The planning of Gray Level Co-Occurring Probabilities (GLCP) is considered as underneath:

$$F_{ij} = \frac{P_{ij}}{\sum_{i,j=0}^{L-1} P_{ij}} \qquad (2)$$

Where $P_{ij} \rightarrow$ Frequency of occurrence between two gray levels, $L \rightarrow$ Number of quantized gray levels, i and $j \rightarrow$ Displacement vector for the specified window size.

GLCMs achieve more than a couple of measurements from them holding the gray co props function. These statistics offer data about the texture of an image. The insights like Energy, Entropy, Cluster shade, Homogeneity, and Maximum probability are separated from thepreprocessed image.

4.3 Cloud classification Model using ML classifier

For the cloud classification issue nearby, we utilized an arrangement of feature factors to the classifier model. The issue of cloud data classification from satellite imagery utilizing neural systems is utilized here. In this technique, a neural- network based radial basis function cloud classification framework is proposed. The features from both the unmistakable and channels were then combined together and fed to a neural- network classifier.

4.3.1 Radial Basis Neural Network (RBNN)

A Radial Basis (RB) function neural system has an input layer, a hidden layer, and an output layer. The neurons in the hidden layer contain Gaussian trade functions whose outputs are contrarily corresponding to the partition from the point of convergence of the neuron. The principal thought is that an expected target estimation of a thing is most likely going to be about the same as various things that have asecure assessment of the indicator factors. The simple design of RBF-NN shows up in Figure 3.

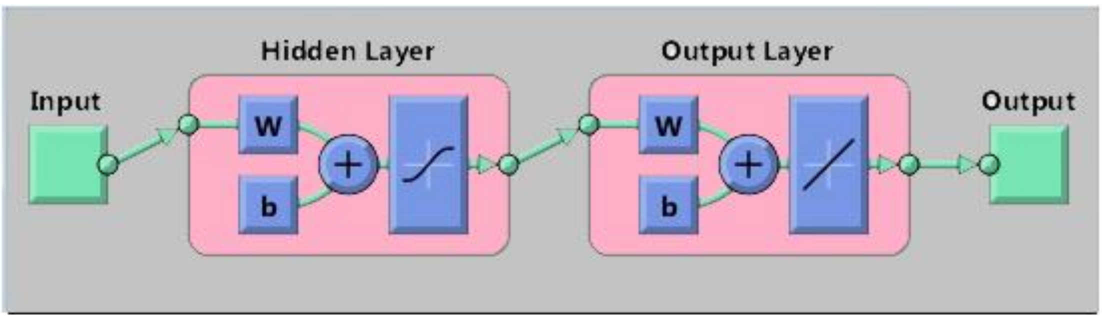


Fig 3: RBF kernel

RBF parameter optimization handlesGenetic-based Harmony Search (GHS) Optimization is used. RBF systems were stated into the neural system composing with the help of Broom head and Lowe. On the conflicting to build up models (multilayer perceptrons, et cetera.), it is a framework with close-by units that was charmed with the help of the occasion of different neighborhood reaction segments in the human brain.

Objective function

The system is normally placid of three layers: an input layer, a singlehidden layer of nonlinear preparing neurons, and an output layer. The inconspicuous layer changes the data from the input space to the hidden space with the help of a non-straight function. An organized Gaussian capacity commonly utilized as the radial basis function as underneath:

$$\Phi_i(e, c_i) = \exp\left(\frac{-\|e - c_i\|_2}{r_i^2}\right) \quad (3)$$

Where $e \rightarrow$ input parameters, $r_i \rightarrow$ signify the radius of the i^{th} node, $c_i \rightarrow$ center vector for the neuron. It has been watched that if enough units are expressed, an RBF-NN can dubious any multivariate consistent capacity as predicted [27]. Accordingly, the focal issues in RBF NNs configuration stretch presenting a number of inconspicuous neurons to utilize and their concentrations and radii.

RB-NN can be created by two stages:

- Control the parameters of radial basis function, i.e., Gaussian concentration and range, in which k-meansclusteringsystem was regularly utilized.
- Control the output weight W with the help of supervised learning technique; in that minimum mean square or recursive scarcest square was consistently utilized.

The fundamental stage is amazingly basic, as the amount of inconspicuous and zone of thecenter will inconvenience the execution of RBF-NN. This investigation work GHS used to propel the weights of RBF work – NN that fitness function achieves most extreme accuracy with exact satellite image classes.

4.3.2 Optimization model for cloud classification

This cloud classification model improves RB kernel two inspired optimizations used, for example, Genetic Algorithm (GA) and Harmony Search (HS). At first, this HS procedure is another sort of metaheuristic algorithm representing a musicians’ way to deal with discovering agreement while playing music. In particular, the procedure by which the performers (who have never played together) quickly refine their individual ad lib through variety bringing about an aesthetic harmony, its appeared in figure 4.

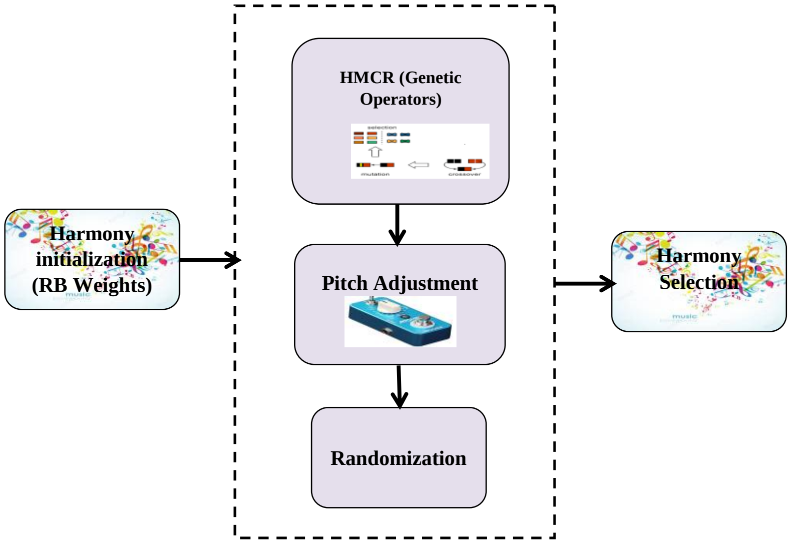


Fig 4: Genetic-based harmony search process

Regularly the Harmony Memory considering Rate (HMCR) considered as 0 to 1, our proposed model utilizing genetic operator's crossover and mutation is used to pick the memory. The system or ventures for GHSO demonstrated as follows.

Step 1: Initialization Process

This movement instates RBF neural network parameters are hidden neurons, sweep, centers and weights the Radom esteems between - 10 to +10. The average HS parameters are Harmony Memory Size (HMS) or the quantity ofsolution vectors in the harmony memory;Pitch Adjusting Rate (PAR)

Step 2: Fitness Evaluation Process

In each square of the image we continue to discover the fitness in a partitioned part and here the fitness is the most extraordinary precision of the divided part. The accuracy is discovered using the parameters, for instance, True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN).

$$F_i = \max\left(\frac{TP+TN}{TP+TN+FP+FN}\right) \quad (4)$$

Step 3: Initialize the HMS and HMCR

In this progression, the Harmony Memory (HM) matrix is loaded with the same number of haphazardly created solution vectors as the extent of the HM, and arranged by the estimations of the objective function.

Step 4: Find HMCR

The HMCR is characterized as the probability of choosing a component from the present HM individuals, and 1-HMCR is, accordingly, the probability of producing by utilizing crossover, mutation, and selection process.

Crossover: The crossover operation has numerous strategies to deliver the offspring. They are one point, two points, uniform, and arithmetic crossover, in these procedure single point crossover is utilized.

Mutation: While recombination operates on at least two parental chromosomes, mutation locally however haphazardly alters a solution. Mutation is a genetic operator used to keep up ageneticassorted variety from one era of a populace of genetic algorithm chromosomes to the following which is undifferentiated from natural mutation.

Selection: At closing stages of the mutation, the new chromosomes are produced for the new solution sets. At that point, assess and refresh the fitness esteem for the new solutions.

In view of this determination discover HMCR estimation of HS updating procedure.

Step 5: Improvise a new harmony

Generating a new harmony is called improvisation. In the memory consideration, the value of the first decision variable R_1^1 for the new vector is chosen from any of the values in the specified HM $(R_1^1 - R_1^{HMS})$range. The HMCR from thecrossover and mutated solution values is the rate of choosing one value from the historical values stored in the HM, while $(1-HMCR)$ is the rate of randomly selecting one value from the possible range of values.

$$R_i^{'} = \begin{cases} R_i^{'} \in \{R_i^1, R_i^2 ....R_i^{HMS} & with \quad probability \quad HMCR \\ R_i^{'} \in R \quad with \quad probability & (1-HMCR) \end{cases} \tag{5}$$

Each component acquired by the memory consideration is inspected to decide if it ought to be pitch-balanced. This operation utilizes the PAR$\in[0,1]$ parameter, which is the rate of pitch modification as takes after:

$$R_i^{'} = \begin{cases} Adjusting \quad pitch \quad with \quad probability \\ Doing \quad nothing \quad with \quad probability (1-PAR) \end{cases} \tag{6}$$

The estimation of (1-PAR) sets the rate of doing nothing. On the off chance that the pitch alteration decision, $R_i^{'}$ is supplanted as taking after:

$$R_i^{'} = R_i^{'} \pm rand \times bw \quad (7)$$

Where bw is an arbitrary distance bandwidth, $rand$ is a random number in the vicinity of 0 and 1. In this progression, memory consideration, pitch change, or randomization is connected to every choice variable of the New Harmony vector.

Step 6: Update harmony memory

For every new value of harmony,the estimation of theobjective function is figured. On the off chance that the New Harmony vector is superior to the most exceedingly awful concordance in the HM, the New Harmony is incorporated into the HM and the current most exceedingly worst harmony is avoided from the HM.

Step 7: Termination criterion.

On the off chance that getting thegreatest number of extemporizations with most extreme accuracy in cloud classification implies the procedure will be ended. Generally, steps 3 to 6 are rehashed to discover the fitness for refreshed arrangements.

4.4 Cloud Types

From the ML system optimal RBF kernel function based classifies the clouds from satellite images, here three levels: *Low Level:* For this situation, the clouds are primarily composed of water beads. *Medium Level:* These are composed essentially of water beads; despite that, they can likewise be composed of ice crystals when temperatures are adequately low. *High Level:*These are ordinarily thin and white in appearance yet can show up in a brilliant cluster of colors when the sun is Low not too far off.

Training and Testing Process

Training Process

Input: Cloud Satellite Image

Preprocessing: Median Filter is used to preprocessing the input image

Feature extraction: Texture and wavelet feature.

Classifier: Optimal RB-NN

Testing Process

Input: Trained database

Preprocessing

Extract different features of images that we have extracted at the time of Training Phase.

Classifier: If class 1, or class 2 or class 3

5. Result and analysis

The proposed classification system is actualized in the working stage of MATLAB 2016a with ani5 processor and 4GB RAM. Preparing the system utilizing diverse cloud satellite images are considered for the investigation. The execution of the composed classifier was assessed with the assistance of the execution measures. This proposed modelis compared to existing strategies and finds the optimal techniques.

Database Description

The cloud data broke down in this investigation was acquired from the GOES 8 satellite that conveys distinctive channel sensors. The test scenes have shaped more than 140 images cloud satellite images are considered, it contains low, medium and high-levelclouds. Since the reason for this examination was to look at the performance of cloud classification framework for specific ranges without considering the temporal changes of the data. These images covered the same geographical districts and were gotten amid practically a similar time of the day. Test image database appeared in beneathfigure.

Fig 5: test image database

Performance metrics

This proposed classification model below mentioned parameters are evaluated

TP: True Positive FP: False Positive

TN: True Negative FN: False Negative

Precision:The precision assesses what number of the images are classified to be Positive are really Positive by methods for the condition.

$$\Pr e = \frac{TP}{FP + TP} \quad (8)$$

Accuracy:It is a measure which decides the probabilities that how may comes about are precisely classified the recipe appeared in condition (4).

Sensitivity: Sensitivity is a measure which decides the probability of the outcomes that are genuine positive as 'that images as in one class'.

$$Sen = \frac{TP}{TP + FN} \quad (9)$$

Specificity:It is a measure which decides the probability of the outcomes that are truenegative as 'that input image as low or high or medium'.

$$Spc = \frac{TN}{TN + FP} \quad (10)$$

Table 1 Feature Values

Images	Feature Vector	Accuracy (%)
1	2608.96	91.22
2	1756.22	84.22
3	525	89.22
4	98.25	93.22
5	482.2	94.55

Table 1 delineates the feature values for satellite cloud images. In this table shows the five sorts of cloud images and discover the accuracy for specific feature vector values. Feature extraction is the vital stage for each classification to classify the image pixels to various sorts. In this investigation take a few features like Texture, Wavelet, and GLCM. These systems can classify the images as low level, medium, and high level. In light of the satellite image 1, the feature vector is accomplished as 2608.96 and their accuracy as 91.22%, for thesecond image the feature vector is 1756.22, at that point, the accuracy for that image happens 84.22%. Thus, different images additionally get thesame kind of feature vector esteems and accuracy; chiefly for fifth cloud image the feature vector achieves 482.2; however the accuracy is 94.55%. Compared to other four images this image can acquire the greatest accuracy. At long last, the feature extraction can remove the features with optimal accuracy.

Table 2: Performance evaluation

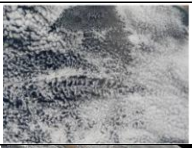
Input images	Precision	Accuracy	Sensitivity	Specificity
	91.22	96.33	83.2	65.33
	85.22	98.22	75.22	75.55
	86.222	97.322	79.2	90.2

Table 2 demonstrates the performance evaluation for cloud images. Here the performance measures, for example, precision, accuracy, sensitivity, and specificity for all the three input images are considered as low, medium and high cloud images. In the principal image that is low-level cloud image, the exactness for that image achieves 91.22%, accuracy of 96.33%, precisionof 83.2%, and specificity of 65.33%. At that point the performance assessment for thesecond image as medium level here the precision achieves 85.22%, accuracy accomplishes 98.22%, sensitivity achieves 75.22%, and specificity of 75.55%. Coming to abnormal state cloud image the precision achieves 86.22%, accuracy gets 97.322%, sensitivity as 79.2%, and specificity accomplishes 90.2%. In view of these performances measurevalues, the greatest precision gets in thelow level image, high accuracy in themedium level image, optimal affectability in thelow level image, most extreme specificity accomplishes in abnormal state cloud image. The performances are assessed in view of their optimization systems.

Table 3: Cloud class based Results

Testing Images	Cloud Level	Validation 1	Validation 2	Validation 3	Precision (%)	Accuracy (%)
30	Low	22	5	3	78.22	97.37
30	Medium	15	12	3	65.22	95.66
30	High	5	17	8	80.22	98.77

Table 3 demonstrates the satellite-based cloud image classification results. From that cloud images, precision value is figured by the assistance of classification systems. The cloud images are classified in light of three sorts i.e. low, medium and high. In first image here 30 testing images taken for estimation reason, from that testing images there is 22 low-level cloud images, 5 medium images, and 3 high-level images the precision for these images achieve 78.22%. In image 2, here 15 low-level images, 12 medium level images and 3 high-level images are classified. The precision for the second sort of image is 65.22%. At that point for image 3, the precision is 80.22%, in this procedure, there are 5 low-level images, 17 medium level images, and 8 high-level images. For the comparison of this three precision esteems the greatest esteem comes to in thethird image. The classification system can classify the images optimal at 80.22% precision.

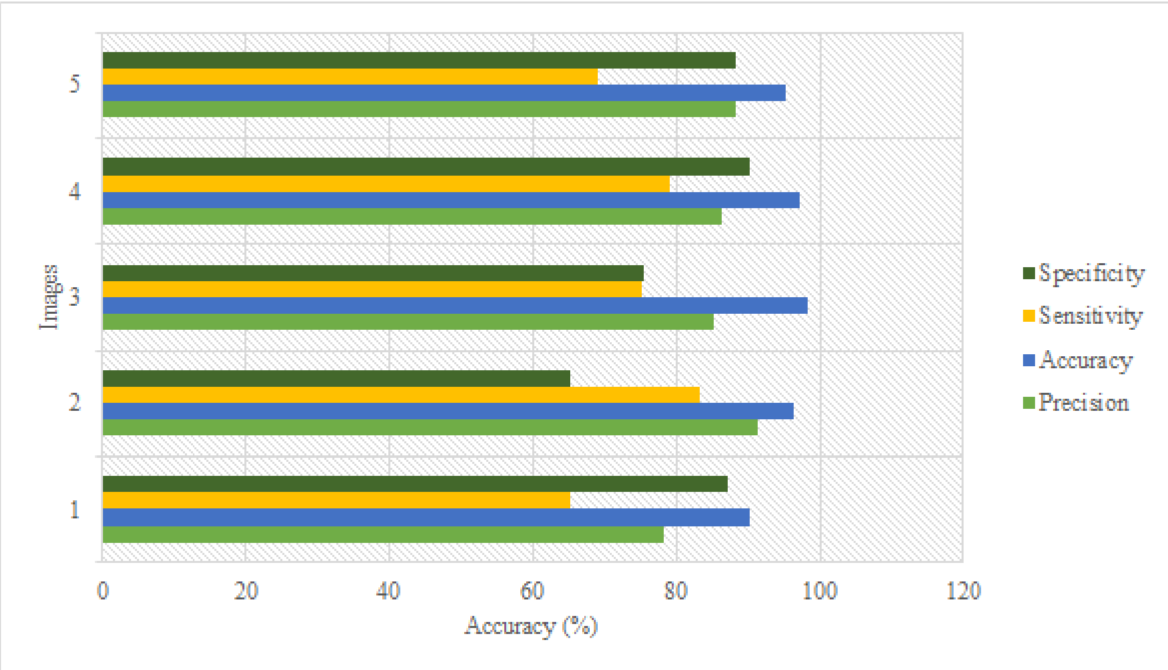


Fig 6: Performance analysis for Proposed Model

Figure 6 outlines the performance analysis of proposed strategy. This chart finds the performance measures for specific images. For image 1 the specificity accomplishes 82.6%, sensitivity achieves 63.74%, accuracy acquires 85% and precision as 79.32%. The proposed demonstrate accomplishes the performance measures as theoptimalvalue for each image. Here, 5 images are considered for this investigation, likewise, for image 1 every one of the images accomplishes thesame sort of performance values.

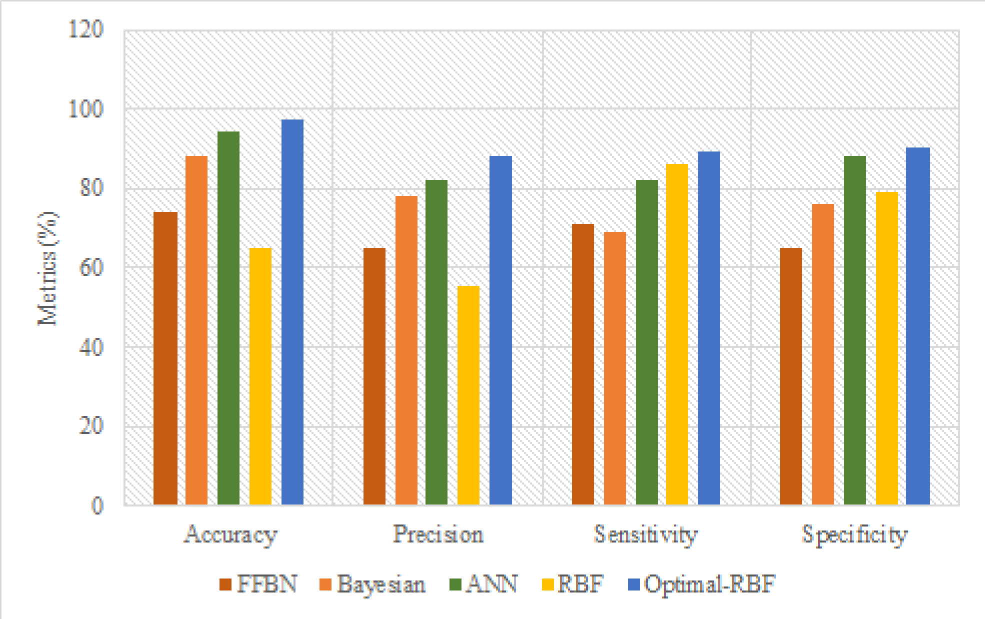


Fig 7: Comparative analysis

Figure 7 envisions the comparative investigation of optimization strategies. This reference diagram finds the optimal methods and dissects the performance measurements, for example, accuracy, sensitivity, Precision, and specificity in percentage. Here, five optimization systems are dissected that is FFBN, Bayesian, ANN, RBF and optimal RBF. From the examination of accuracy, FFBN achieves 75%, Bayesian accomplishes 82.69%, ANN as 63%, RBF gets 62.14%, and Optimal RBF 96.54%. Coming to precision FFBN accomplishes 63.78%, Bayesian as 79.68%, ANN achieves 83.45%, RBF as 73.41%, and Optimal RBF as 83.41%. So also, sensitivity and specificity additionally accomplish a similar sort of results. In view of this comparison of five optimization methods, optimal RBF achieves optimal accuracy, precision, sensitivity, and specificity compared other four strategies.

6. Conclusion

Cloud classification through satellite image is an approach which is essential in numerous atmospheric and Environment studies, for example, weather analysis and forecasting. The classification of satellite clouds image is the best technique for classifying the cloud type as low level, medium level, and high level. The proposed strategy removed the features, for example, Texture, Wavelet and GLCM and predominantly the classification have been finished by Optimal RBF optimization procedures. In cloud classification applications, the Optimal RBF neural systems are viewed as a mapping from the feature to the classes. The examination concludes that the investigation of performance measurements that is accuracy, sensitivity, specificity, and precision are performed better when compared to FFBN, ANN, Bayesian, and RBF strategies. The optimization algorithm GHSO optimizes the structure and finds the optimal value. It performs most extreme accuracy as 97.32%, thesensitivityof 83.2%, specificity achieves 90.2% and precision accomplishes 91.2%. The optimal methods can perform high classification rate and keeps up their performance values to predict the climate change and weather forecasting.

Application:This proposed classification technique has been used as potential aviation safety application for turbulence detection. Nevertheless, the algorithm here introduced is very intense and suitable for research purposes. These techniqueshelp to get information about theatmosphere, ocean and cloud conditions in all weather; in addition, it has great significance for weather monitoring and disaster prevention and alleviation. The satellite cloud image analyses are used in theagricultural field, environmental and resource management.

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