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Novel Ensemble-Based Deep Learning Model for Remote Sensing Images Classification

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***Abstract*— Scene classification from remote sensing images is still defined as an ill-posed problem. Deep learning models outperform the competitive techniques but suffer from various issues. These issues are it has been observed that the majority of existing deep learning models such as deep convolutional neural networks, etc. suffer from premature convergence issues. It limits the performance of scene classification. The tuning of the hyper-parameters of deep learning models is still a challenging issue, therefore, automating the tuning of these parameters is desirable. Deep learning models may also suffer from overfitting issues. To overcome these issues, a novel ensemble-based deep learning model is used to classify the scenes in remote sensing images. To tune the hyper-parameters of the proposed scene classification model, the particle swarm optimization algorithm is also used. The comparative analysis show that the proposed model outperforms the existing model.**

Keywords—Deep learning, Particle swarm optimization, Hyper-parameters, Remote sensing images

I. Introduction

Multiple remote sensing images are usually converted into a digital system, followed by generation of images for study by the microprocessor. Multiple image processing techniques find application in many areas like medical fields, military fields, communication field, etc. In the mid-60s, the general remote sensing impetus was transmitting images to receiving stations by using unnamed satellites, but the visibility of the image was poor. Landsat satellite was launched. It sent the global images continuously with better visibility and quality. Then, after many of the satellites came in continued launching by developing supercomputers, faster peripherals which are better suited to digital image processing.

Remote sensing image fusion has been developed by multiple satellite images with many variations in frequency. The reflection of the earth satellites gives data remaining in various domains of the Electromagnetic (EM) spectrum, such as high spatial resolution and spectral resolution. Different characteristics of the fused image provide better measurable data, which is not obtained in individual characteristic images.

A. *Typical digital image*

An image relates to two-dimensional coordination varying in brightness, such as I(x, y). Latest digital technology is used operating multidimensional signals along with certain capabilities ranging from simple digital circuits to advanced computers. Images can be categorized as: Processing: from input image to output image. Analysis: of the input image with measurements of the output images. Understanding: this is characterized from an input image to a high-level description of the output image.

B. *Image Classification*

In the classification technique, image pixels are grouped for extracting information effectively. There exist two methods of classification technique, namely, supervised and unsupervised. In monitored classification. Personality and spot of some of the land-cover types, such as for example cement, ice, sand, vegetation, water, soil, rock, etc. are known a priori through a combination of subject function, analysis of aerial photography, maps, and personal knowledge, whereas in unsupervised learning, test information hasn't been branded, classified, or grouped. The analyst efforts to discover certain sites using remotely believed information that signify homogeneous samples of known land-cover types. These places are called as instruction sites since the spectral faculties of the known places which are used to train the classification algorithm for final land cover mapping of rest of the image. Features are produced for every single instruction site. Every pixel both within and external these instruction sites are then considered and assigned to the type which includes the best likelihood membership. Several well-accepted standard supervised classification techniques like minimum distance, parallelepiped, and maximum likelihood classifier. multispeed-based voting approach, Support Vector Machine.

1) *Drawback of Supervised Classification*

All above-mentioned methods suffer from some of its own demerits. Minimum-distance classifier is capable to capture circular or homogeneous data only, whereas in a parallelepiped classifier, many pixels of the original image may be assigned to unknown classes. This problem may be solved by increasing the interval length, which can lead to the overlapped classes problem. Sufficient number of training samples of each class are

Fig. 1. **digital image processing**

C. *Deep Learning*

machine learning algorithms have shallow structured architectures such as Hidden Markov Models, Support Vector Machines, Multi-perceptron Neural Networks with one hidden layer. The shallow structure is effective in solving well-constrained problems but limited in modelling complex problems which require more layers of nonlinear processing such as image processing and human speech processing. The concept of deep learning originates from artificial neural networks. However, neural network learning algorithms tend to be trapped in poor local optimum due to the vanishing gradient problem if a neural network model goes deeper. To overcome the limitation of back-propagation in training deep neural networks, Hinton et al. proposed a greedy layer-wise learning algorithm [70] to pretrain the deep structure. This layer-wise greedy learning algorithm fundamentally changed the way neural network

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weight updating mechanism, which made it possible to learn a larger and deeper neural network.

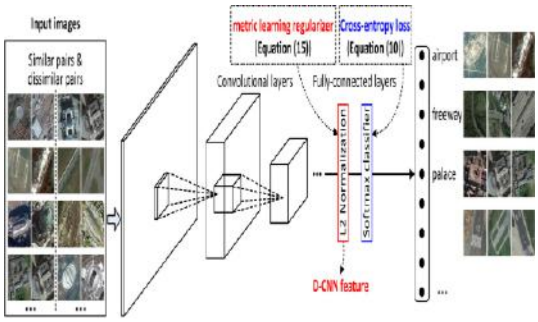

Fig. 2. **Illustration of the core idea of the proposed D-CNN method.**

To handle the challenges of within-class variety and between-class likeness, we propose to learn D-CNNs by optimizing a fresh objective function. Aside from reducing the cross-entropy loss, we also impose a metric understanding regularization expression on the CNN characteristics to enforce the D-CNN product to become more discriminative. Ergo, in the D-CNN function space, the pictures from the exact same world type are as close as you possibly can and the pictures of various courses are as a long way away as possible.

II. Literature Review

Lu et al. (2016) [1] designed a Markov random field (MRF) to classify the remote sensing images. Jia et al. (2018) [2] designed a multitask sparse logistic regression fusion model. Wang et al. (2015) [18] have shown that the intended PAN based adaptive CS and implementing a Particle-Swarm-Optimization (PSO) process to resolve the single opposition optimization issue. As compared to the CS method, the PSO based method performed better in Correlation Coefficient (CC), Mutual Information (MI) and Mean Structural Similarity Index (MSSI).Bhuiyan et al. (2007) [26] introduced the new spatially adaptive wavelet-based Bayesian method by assuming Cauchy and Gaussian pdf for signal and noise, respectively. The dispersion parameter of the Cauchy is estimated using the computationally expensive Gauss Hermite quadrature technique. Ranjani et al. (2011) [27] suggested that the employed multicache intended for indication in addition to a multivariate Gaussian intended for disturbance, called MCMAP criteria working with Two Woods Sophisticated Wavelet Change (DTCWT) by means of using inter in addition to intra-pixel dependencies. Although far more variables have a great therapy for the actual type, accomplishing any closed-down variety MAP solution for the people design can be, on the whole, very hard. Argenti et al. (2012) [28] proposed that the non-homomorphism-based Bayesian methods, equivalent non-logarithmic additive noise model is considered less frequently in the literature (The traditional nonlinear homomorphism (logarithmic) operation leads leads to not impartial approximation of the transmission along with greater complexity of the filtering method. Gu et al. (2017)[29] proposed that the fixed weight load between the center pixel along with border pixels are being used in the common Markov arbitrary discipline regarding switch discovery, which can quickly cause the unnecessary use of spatial neighborhood information. Contour common brand discipline is unable to perfectly distinguish the actual spatial interaction between neighborhood pixels. Zhu et al. (2017) [30] have shown that the cost-free along with open entry to all archived Landsat illustrations or photos throughout offers a wholly modified clear way of employing Land set data. Lots of fresh switch discovery algorithms depending on Landsat period string are developed, Most of us current all-inclusive evaluation of four main reasons of switch discovery research depending on Land set period string, which include frequency, preprocessing, and algorithms, along with applications.

III. PROPOSED MODEL

This section discussed the proposed model. Fig. 3 shows the proposed model.

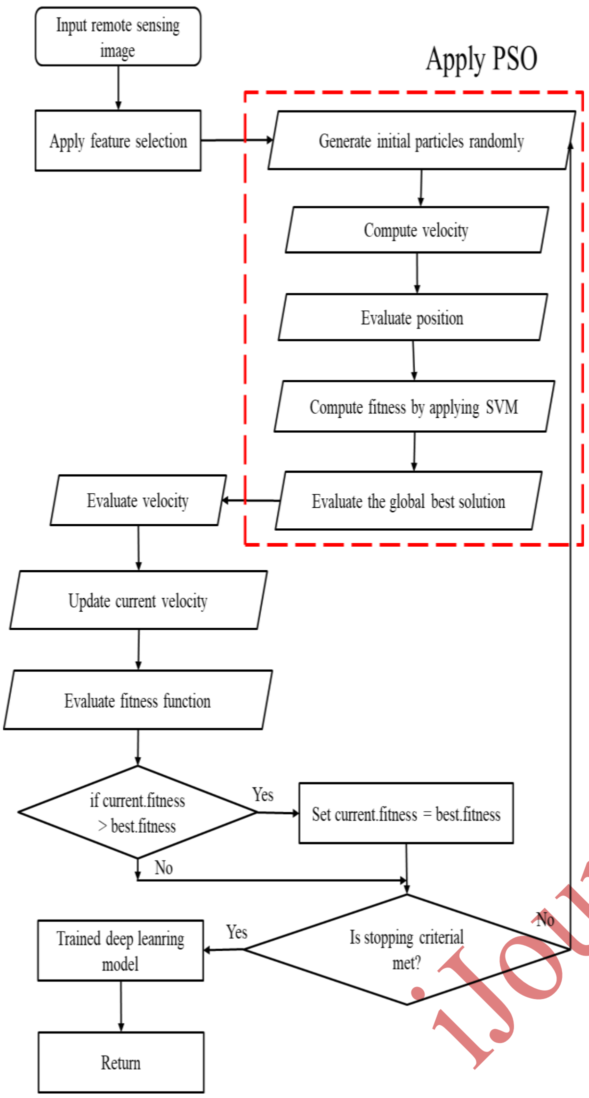

Fig. 3 Proposed model.

Step 1: Load the remote sensing image dataset. The feature of the collected dataset is then obtained. Thereafter, the dataset is divided into training and testing fractions.

Step 2: Select potential feature of the dataset for training purpose.

Step 3: Initialize the random particles to optimize the SVM model.

Step 4: Compute velocity and position values of PSO.

Step 5: Evaluate fitness of particles by using the initial parameters of SVM.

Step 6: Compute global best (gbest) and particle (pbest) to select the solutions.

Step 7: Recompute the velocity and fitness values of selected solutions. The objective is to select gbest solution.

Step 8: If termination criteria get satisfied then we will train the deep learning model otherwise we will repeat steps 4 to 7.

Step 9: Return the train model for classification purpose.

IV. PERFORMANCE ANALYSIS

This section discusses the various performance metrics used in this research work to evaluate the performance of the existing and proposed image captioning models. The proposed algorithm is tested on various stages. The algorithm is applied using various performance indices like Accuracy, F-measure, Sensitivity, Specificity, Kappa statistics Testing time.

A. *Accuracy*

Accuracy is a well-known quality metric used for evaluating the ratio of the total number of correctly classified captions over the total number of captions. Confusion matrix (so-called error matrix) is used to evaluate the accuracy analysis. The accuracy (Ac) is mathematically defined as:

$$A_c = \frac{T_p + T_n}{T_p + T_n + F_n + F_n}$$

Here, $T_p, T_n, F_p,$ and F_n defines true positive, true 185 negative, false positive, and false negative values, respectively. A_c 2 [0; 100]. A_c Models toward 100 is desirable.

TABLE I. **ACCURACY ANALYSIS**

Images	Existing	Proposed
Im1	0.9827	0.9917
Im2	0.9716	0.9766
Im3	0.9749	0.9774
Im4	0.9747	0.9812
Im5	0.9786	0.9856
Im6	0.9719	0.9759
Im7	0.9753	0.9773
Im8	0.9829	0.9899
Im9	0.9807	0.9847
Im10	0.9788	0.9808
Im11	0.9798	0.9873
Im12	0.9786	0.9825
Im13	0.9726	0.9786
Im14	0.9766	0.9816
Im15	0.9755	0.9825

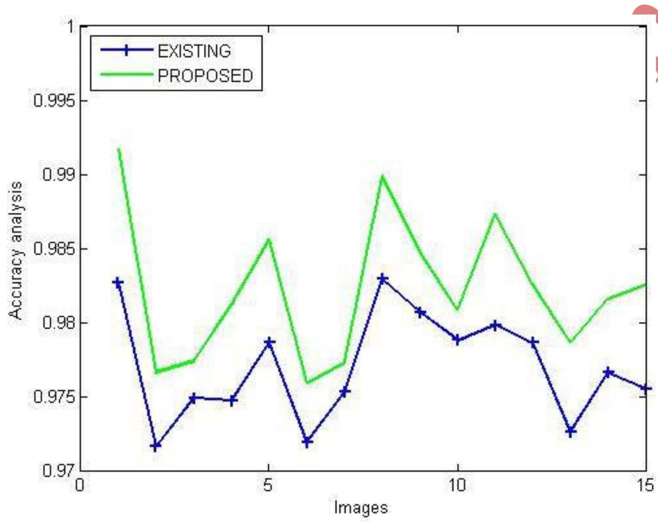

Fig. 4 Accuracy analysis of the proposed model

Table I and Fig. 4 show the accuracy analysis of the proposed remote sensing classification model. It shows that the proposed model outperforms the competitive models in terms of accuracy. The proposed model achieves an average improvement of 1.1342 % over the existing model.

B. F-measure analysis:

Accuracy is not found to be an efficient measure for biased data. It means if in the input data, any class positive to negative is more, then the accuracy is not accepted as a significant measure. Therefore, we have considered a F-measure to evaluate the weighted mean Precision (p) and Recall (r). Thus, it considered the values of both false positives and negatives in the evaluation. Mathematically, $F1$ Score is defined as:

$$F1\ score = 2 * \frac{r * p}{r + p}$$

Here, p can be computed as:

$$p = \frac{T_p}{T_p + F_p}$$

r can be estimated as:

$$r = \frac{T_p}{T_p + F_n}$$

F1 score needs to be maximized.

TABLE II. **F-MEASURE ANALYSIS OF THE PROPOSED MODEL**

Images	Existing	Proposed
Im1	0.9815	0.9865
Im2	0.9849	0.9929
Im3	0.9726	0.9735
Im4	0.9761	0.9826
Im5	0.9845	0.9885
Im6	0.9856	0.9929
Im7	0.9735	0.9818
Im8	0.9806	0.9821
Im9	0.9826	0.9901
Im10	0.9795	0.9887
Im11	0.9807	0.9827
Im12	0.9739	0.9814
Im13	0.9799	0.9814
Im14	0.9702	0.9772
Im15	0.9714	0.9779

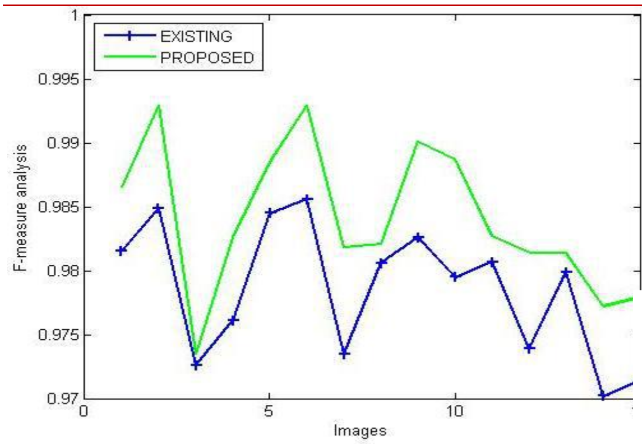

Fig. 5 F-measure analysis of the proposed model

Table II and Fig. 5 show the f-measure analysis of the proposed remote sensing classification model. It shows that the proposed model outperforms the competitive models in terms of accuracy. The proposed model achieves an average improvement of 1.2849 % over the existing model.

C. Sensitivity analysis:

Sensitivity evaluates the degree of senstivity by using TP and FP values as:

$$Sensitivity = \frac{TP}{TP + FP}$$

TABLE III. **SENSITIVITY ANALYSIS OF THE PROPOSED MODEL**

Images	Existing	Proposed
Im1	0.9795	0.9855
Im2	0.9814	0.9849
Im3	0.9844	0.9894
Im4	0.9815	0.9989
Im5	0.9787	0.9827
Im6	0.9721	0.9741
Im7	0.9808	0.9858
Im8	0.9718	0.9773
Im9	0.9741	0.9781
Im10	0.9762	0.9822
Im11	0.9719	0.9774
Im12	0.9756	0.9795
Im13	0.9727	0.9802
Im14	0.9705	0.9747
Im15	0.9757	0.9835

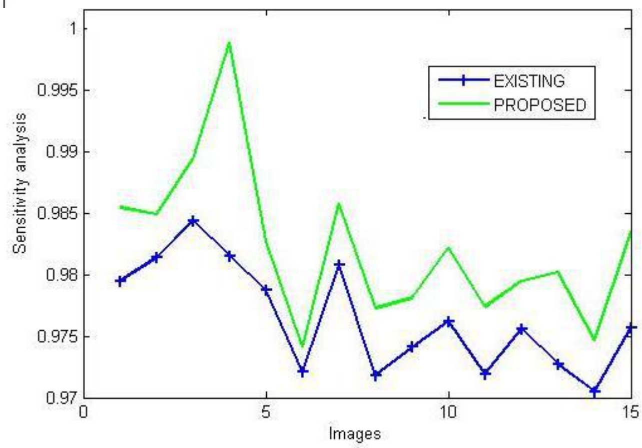

Fig. 6 Sensitivity analysis of the proposed model

Table III and Fig. 6 show the sensitivity analysis of the proposed remote sensing classification model. It shows that the proposed model outperforms the competitive models in terms of accuracy. The proposed model achieves an average improvement of 1.2931 % over the existing model.

V. CONCLUSION

In this paper, a novel classification model is proposed for remote sensing images. Initially, we have loaded the remote sensing image dataset. The feature of the collected dataset has been then obtained. Thereafter, the dataset has been divided into training and testing fractions. Potential features of the dataset for training purpose have been selected. Thereafter, random particles were initialized to optimize the SVM model. Compute velocity and position values of PSO. Thereafter, fitness of particles has been computed by using the initial parameters of SVM. Global best (gbest) and particle (pbest) have been utilized to select the solutions.

Thereafter, recompute the velocity and fitness values of selected solutions. The objective was to select gbest solution. Depending upon termination criteria final trained model was achieved. Comparative analysis indicate that the proposed approach outperforms the competition models.

In near future, we will use other metaheuristic techniques to enhance the work. Also, deep transfer learning models can be used to extend the proposed work.

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