JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Optimized Deep Learning Framework forScene Classification on UAV Images

Mrs. Reshma M [1], Dr Manjula S H[2]

[1]Student, [2]Professor
[1, 2] Department of Computer Science and Engineering,
[1, 2] College Name: UVCE

ABSTRACT - With the recent advancement triggered in the field of the automated territory control and monitoring, the usage of the remote sensing acquisition has reached a new level of acceptance. Furthermore, the unmanned aerial vehicles (UAV's) based automation also gained popularity with respect to real time application in scene identification, land classification etc. The reason for the manifestation of UAV is their ability to acquire high resolution data irrespective of the geographical areas even if it is inaccessible. The size of the UAV and its flight capability with ease of use has been manifested as the reason for the consideration of the detailed image acquisition even with limited coverage zones. The adaptation of the image processing techniques on the UAV images for the application-oriented environment is found to be a surging research with the growth in the machine learning, artificial intelligence and deep learning because of the abstraction which can be achieved through diverse features of the UAV images without the assistance of human. However, the potential research field encountered variety of problem in deep learning techniques dedicated for the UAV scene classification system because of improper image processing (pre-post), computational redundancy in the deep learning framework, uncertainties in the feature extraction and GUI for the deployment. In addition to the framework issues, the hyper parameter tuning in the deep learning algorithms were also limited with its non-dominant solution. In order to overcome the aforementioned issues with UAV scene classification, in this research a deep learning framework optimized with particle swarm optimization algorithms was developed with marginal processing techniques and feature extraction paradigm. To evaluate the performance of the proposed model, two open-source UAV datasets were used. The experimental results proved in comparison to all existing methods that the proposed PCNN framework has a maximum accuracy of 98.7%. The proposed model has been successfully deployed for usage in a GUI with the help of serialization for scene categorization in real time.

KEYWORDS – C*onvolutional neural networks Deep learning, Machine learning, Particle Swarm Optimization, UAV.*

I. INTRODUCTION

Remote sensing is a wide sense concept with its application handed over in most of the areas ranging from object identification, land classification, scene classification, object recognition, monitoring, and energy over area measurement, information gathering etc which helps in application-oriented fields such as military, agriculture, medicine etc. To understand the importance of remote sensing, it is mandatory to know the variants on to which it is adapted. They are active way of remote sensing and passive way of remote sensing. In active sensing, the signal is emitted through the sensing devices such as satellites, aircraft sensors and the reflected pulse from the objects is analyzed for evaluation. Active sensing technique is considered advantageous because it can be used in day or night without depending on any geographical constraints, or direct contact [8-10]. The problem with the active way of sensing is originated only from its demand on the energy source of the pulse emitted through the sensors. Some common examples of the active remote sensing techniques are Radars, Light Detection and Ranging (LiDAR). In both these use cases, the radio waves are emitted through the sensors to fetch information about the target. On the contrary, passive remote sensing technique acquire information from the target intended on the energy originated from the target itself such as sun ray, electromagnetic energy etc. The exploitation of the target energy source makes its more accessible and less energy demanding over the active remote sensing techniques [2]. One among such passive remote sensing technique is UAV. UAV are originally developed for usage in the military for the surveillance and are designed to be "on-demand" technique. The initial use case made it with many characters starting from economical cost, easy usage, customization ability, etc. The imaging sensors placed on the UAV are also found appropriate according to the requirements. In addition to its surpassed usage in military, it is found optimally enough to be considered in the supporting satellites to cover the demographic areas which are inaccessible with its ability to detailed scanning procedure. They are able to collect high resolution spatial images. The flexibility of the UAV with remote control made it possible in complex acrobatic group flights as well. Even with the problem of limited coverage zones, the UAV maintained its advantage by collecting the data in a timely manner which makes it wide coverage possibility. With the aforementioned potentialities, UAV are opted over airborne platforms for the data acquisition. The application of the UAV images among the research community is found to be standout. Some of the use cases are listed below. UAV framework for the cartography domain over the urban or rural location is presented initially [1] from the UAV imagery. With the application of any pattern matching algorithms, cadastral plain over the terrain areas can be easily identified. UAV imagery is also used for 3-D mapping system with the images collected from UAV with the support of the laser scanner and inertial measurement unit, and Global positioning system [2]. The active way remote sensing technique such as RADAR is also made possible with the help of UAV system with its hand over map-drift algorithm [3]. In addition to passive replacement, vision path planning system is also made possible with UAV especially in GPS denied environment. [4] Navigation systems are also deployed based on UAV drones collectively for the indoor environments for industrial applications [5]. The application of UAV in inspection in recent years even for the crowd management is found feasible [6]. Furthermore, online inspection video monitoring system for industrial installations based on aerial collaborative communications between small UAVs. Concerning public safety, UAV aerial support provides a very adequate system to acquire information in unreachable areas. Aside from guaranteeing the safety of human operators from direct contact with danger in emergency from the aforementioned application, it is evident that for the scene / land classification UAV imagery are found notable [7].

In recent years, the advancement with the artificial intelligence and machine learning has increased the application of the UAV in monitoring system and recognition/classification system [11-13]. In UAV scene classification using deep learning algorithms [26-28], the problems persist starting from the processing techniques employed, with parameter tuning issue and usage issues. With aforementioned issues as core, the proposed framework model is developed in this research with reduced computational redundancy and ease of use. In regard to ssolution on existing system; following contributions are made in the proposed model:

- The first one recalls the issues related to the image processing techniques. In the proposed framework in addition to the original UAV images, different imaging variants such as Hue Saturation Value images are also equipped for the scene classification by keeping the satisfactory classification accuracy in mind.
- The second one is that adaptation of better feature extraction algorithms which covers the entire information about the image pixels. The features considered in the proposed work are relevant to scene classification such as shape, texture and edge features.
- The third one is related to multilabel classification. As hinted earlier, usually imagery analysis and classification applications for data acquired over land classification are composed by different scenes. In order to address this, we extend the interest into describing several classes at the same time. Therefore, multilabel approach presents an alternative to the single object description making the classification task more informative and generalized
- The fourth one is centered on the hyper parameter tuning of the features in CNN which is addressed through incorporation of the particle swarm optimization algorithm
- The fifth one recalls the ease of use of the proposed model, for which a ready to executed graphical user interface is developed after the training of the deep learning framework using tkinter.

II. Literature Survey

In this section, the recent literature related to the UAV scene classification is depicted. The research papers considered in the survey are correlated to scene classification irrespective of the imagery with respect to deep learning, machine learning and AI domains. Jing Liang et al. [11], proposes a convolution neural network based paralleled classification of forest trees. In their work, they used hyper spectral image taken by unmanned aerial vehicle. They utilized two types of neural network for classifying spacial features. One-dimensional convolution neural network and two-dimensional convolution neural network are fused for extracting features and for classification task. The predicted result shows that they need to more focus on reducing noise in the image which affects the model performance. Aghila Rajagopal et al [12], projected a system which classifies scenes based on deep learning. The deep residual network is adapted for feature extraction from images acquired by unmanned aerial surveillance system. They deployed self-adaptive global best harmony algorithm to avoid configuration error which cause at manual parameter tuning. They tested the system with two open-source dataset and their technique reaches best accuracy than the other techniques mentioned in their literature.

Christos Kyrkou et al [13], presented a disaster management and emergency response application which capture images using drones. They integrated deep learning with their unmanned aerial vehicle to reduce the complexity of critical decision making in real-time. They analyzed existing approached for image classification and at the end they selected convolution neural network. They developed a real-time embedded system for achieving the goal. They suggested expanding dataset for increasing different scenarios. Leila Hashemi-Beni et al [14], applied a combination of convolution neural network and region growing algorithm for classification flood affected areas from optical imagery. The effective use of convolution neural network classifies the flooded areas. The vegetation area which is not visible in normal digital visualization is extracted using region growing method. They tried to increase their performance of their model by adding data augmentation in training process. The system trained with small dataset and it fails to extract flooded area with dense canopies.

Baojia Du et al [15], used multiple machine learning algorithm for classifying wetland plant communities. The hyper spectral image captured by unmanned aerial vehicle is segmented and features extracted from it for applying machine learning. They used object-based analysis on images which reduced the errors occurred in pixel-based analysis method and can acquire 9 to 15% improvement in the performance. The classification algorithms random forest, super vector machine and random forest are implemented in their system for identifying wetland plant community. Manjit Hota et al [16], proposed a power line detection system using convolution neural network. This system classifies the images with and without power line. The multi-spectral image captured by unmanned aerial vehicle is segmented with different networks like SegNet, U-Net and PSPNet. According to the test scenarios they identified that U-Net performed well than other techniques. The system was not capable of acquire depth information from input image; it slightly affected the system performance. The processing time was very high and they suggest a PC with better specification for increasing efficiency of the model.

Marks Melo Moura et al [17], designed a forest species identification system for Amazon Forest. High resolution images obtained using unmanned aerial vehicle is used in their system for species classification. They used six different species data for training model using Keras and Tensorflow packages. They noticed that the reduction and increase of threshold value affect the performance of model. Bilel Benjdira et al [18], used two deep learning approaches namely YOLOv3 and Faster R-CNN to detect car from image taken by unmanned aerial vehicles. High resolution camera is used for capturing high quality images for processing. The quality of the images increases the performance of the proposed system. They divided the image into different segments with the help of bounding boxes their system locates car position and mark box over it. It achieves more than 95% accuracy for the two models after testing. The images taken in different lighting conditions cannot perform well in their system and also general vehicle categories are only in the dataset. They suggest that the dataset to be added with other categories of vehicles and images with different lighting scenarios for improving accuracy.

Shuang Zhang et al [19], applied a combined approach of extracting high level and low-level features from hyper spectral image to improve the classification performance. For high level features extraction, they used convolution neural network and for low level feature extraction super vector machine is used. Their fusion strategy open ups new ways to improve the accuracy of classification. The major limitation of the proposed system was the misclassification happens for images with shadows. Aghila Rajagopal et al [20], proposed a scene classification model based on deep convolution neural network. The adoption of multi optimization model enhances their system performance. They used two datasets namely UCM and WHU-RS for training model. Their system initially captures high quality videos and converting it to several frames for further processing.

Lihong Su et al [21], investigate the usage of five different convolution neural network models remote sensing image classification. AlexNet, ResNet, VGG16, SqueezeNet and pruned VGG16 are the widely used algorithms adapted in the proposed system. The system classifies coastal beaches from the remote sensing images. The fully convolution approach leads to high impact in the overall accuracy. Giovanna Castellano et al [22], developed a human crowd detection system using aerial image dataset. The system was designed to implement in aircraft and similar platforms to detect safer places for emergency landing. They said that for real-time response a dedicated hardware setup with GPU is required. The computational requirement of their system is very huge. They applied single loss and two loss function for cardinality prediction of crowd. They didn't test their system in real world which increases the practical implementation complexity. The study conducted by Ulzhalgas Seidaliyeva et al [23], solves the linear depth problem by implementing augmentation technique. The proposed system uses ResNet-34 for classification process. Deep convolutional residual neural network is the framework used by them for processing loaded and unloaded images captured by unmanned aerial vehicle. They took more focus on pre-processing step to reduce the chance of data loss. The proposed system only utilized single algorithm and they had a plan to use multiple algorithms like ResNet-50, ResNet-152 and ResNet-101 for classification and it will be useful for comparison of accuracy and loss. Rong Xiao et al [24], introduced a semi supervised approach for segmenting road scenes. There system is capable to extract scene information like vehicles; zebra crossing, road line etc. form the remote sensing images. Semi supervised full convolutional neural network solves the problem with unlabelled data in the experimental dataset they developed. There system shows more accuracy than traditional architecture based on fully convolutional neural network.

From the literature, it is evident that most of the existing systems faced potential issues in the hyper parameter tuning even with better output. The computational complexity and usage of the system setup with graphical processing unit is made mandate. Moreover, the spatial importance to the image processing techniques is not considered with the work relying only on the nominal data set.

III. Methodology

In this section, we present the methodology of the proposed model for the UAV scene classification. We presented the methodology as a hierarchical paradigm including

- Pre processing
- Feature Extraction
- Proposed CNN
- PSO Optimized CNN
- Post Processing
- GUI based Execution

This paper proposes a P-CNN algorithm technique for managing the classification accuracy. Block diagram of the overall system is shown in Figure 1.The information about individual unit of the paradigms depicted below. The pre-processing technique is opted first over the collected open-source images to make it uniform and trans-formative in nature. The pre-processing does not rely on any image segmentation technique or filtering since its working on the high-resolution UAV images. The processed images are given to feature extractor where useful information for classification is extracted using image processing algorithm. The extracted features are fed as input to CNN for training. The model features from the last pooling layer of the CNN are taken out and given as input to PSO CNN for better selection and are then passed to classification learning for the training and testing to achieve better accuracy Moreover, the PSO is also used for the selection of optimal tuning parameters during the course of training.

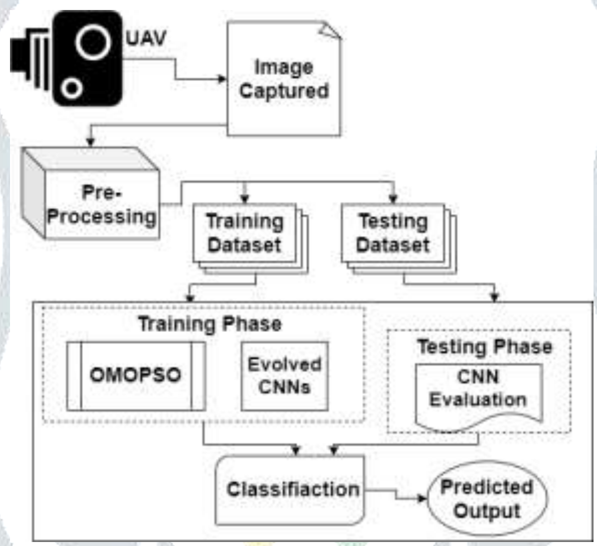


Figure 1. The flow chart of the system

A. Pre-processing

The rational motive for the consideration of pre-processing technique is not filtering, but also to include different variants of image source for the classification training process. In rare instances, the scenes acquired by the image sensors on a UAV may not be clear. The possible object areas are further processed in the following steps. This phase enables the frame region to be processed and, in some cases, to alter or skip frames with no possible object areas. Since some images will not be taken under proper illumination, we are also using HSV images as shown in Figure 2.So, we don't miss necessary features. The images from two different sources are used which are deliberated in the data description section which are of different sizes. By employing the pre-processing technique all the images are made of uniform size.

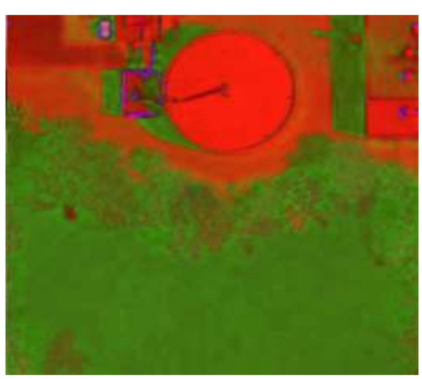


Figure 2. HSV images

B.Feature Extraction

The process of creation of the feature space by mapping the image pixels or groups is called feature extraction. The importance of the feature extraction is pivotal as it is the deciding factor in the performance of the classifier. Some of the image processing algorithms employed for the feature extraction are Haar, Scale Invariant Feature Transform, Histogram of Gradients, Local Binary Pattern Histogram etc. The recognition framework with better feature descriptors have enabled the capability of the deep and improved neural network architectures in the recent years [29-33]. In general, beside image processing algorithms, generic feature extractors are also found in modern day CNN [30]. The reason for the consideration of the feature extraction technique in the proposed model is to reduce the number of resources for training without losing any critical or relevant information from the images. For shape features we are using canny edge detection as shown in Figure 3. As the name suggests, the canny edge detection uses multi-stage algorithm [32] to detect edges in the images which is important in scene classification. The second set of features is associated with texture of the image pixels. For the texture features we are using Haar and LBP. LBP is used to obtain image miniature features as shown in Figure 4 and to get overall features as shown in Figure 5 which helps to classify easily. LBP has been found to be a powerful feature for texture classification; it has further been determined that when LBP is combined with the Histogram of oriented gradients (HOG) descriptor, it improves the detection performance considerably on some datasets.

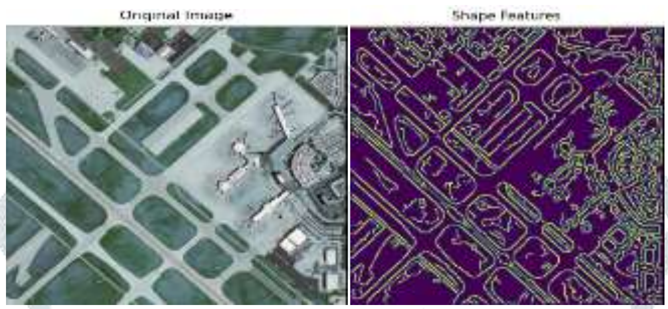


Figure 3.showing the shape features extracted from the image

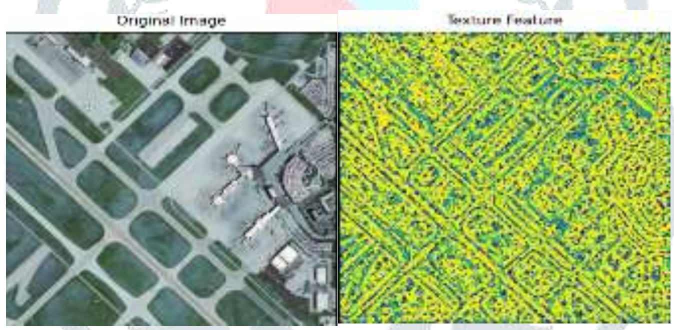


Figure 4.showing the texture features extracted from the image using LBP

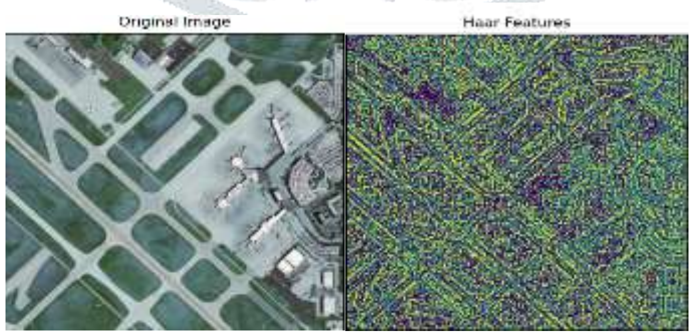


Figure 5.Showing the texture features extracted from the image using HAAR

C. Proposed image classification algorithm

This section depicts the CNN created in the proposed model for the UAV scene classification. CNN is nothing more than a normal feed forward neural network without backward propagation capability. The CNN consist of nominal three layers input, hidden layer and output layer. The layers of the proposed CNN model are depicted in Figure 6. Operation complexity of the CNN originates from multiplication of the input with network weight, transformation and error calculation. Different from the regular neural networks, a neuron in a CNN is only connected to a small number of neurons in the previous layer that are called local receptive fields. Furthermore, neurons in a layer are arranged in three dimensions: width, height, and depth. CNNs are primarily designed to encode spatial information available in images and make the network more suited to image focused tasks [24]. Regular neural networks struggle from computational complexity and over fitting with an increase in the size of the input. In contrast, CNNs overcome this problem through weight sharing. Weight sharing is a mechanism by which neurons in a Convolution Network are constrained in a depth slice and use the same learned weights and bias in the spatial dimension. These set of learned weights are called filters or kernels. A typical CNN architecture as shown in Figure 6 is a cascade of layers mainly made from three types of layers: the convolutional, pooling, and fully connected layers. After the images are preprocessed in the previous stage, the classification process will take place using CNN model. CNN contains many such layers comprising of (convolution layers, activation layers, batch normalization, pooling layers and a dropout layer) and then followed by flatten and dense layers. For the objective optimizations of the features in the proposed model, the PSO technique is used in the subsequent phase, the PSO technique known as P-CNN is used in the subsequent phase.

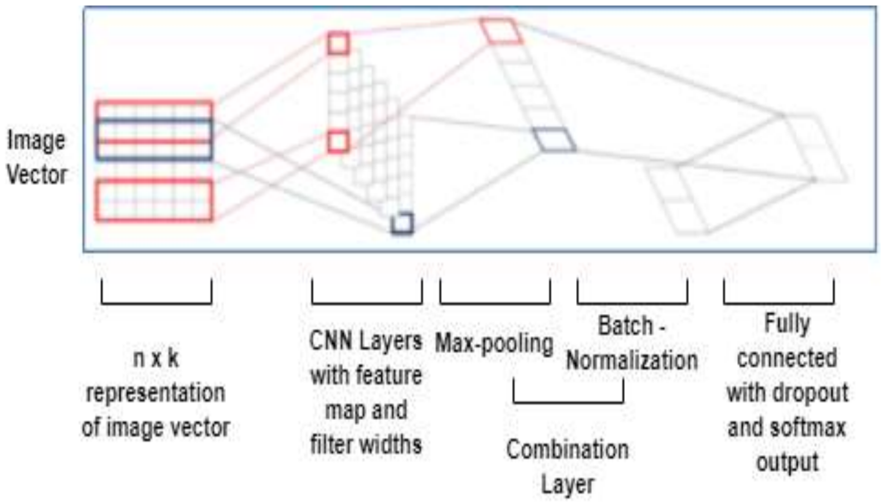


Figure 6. The Basic Structure of the Proposed CNN

D. PSO Optimized CNN

Figure 7 depicts the PSO optimization in the proposed deep learning framework. PSO is a population-based algorithm that works on the idea and inspiration of bird flocks, fish schools, and other swarms. The name "Particle Swarm Optimization "comprises three words: Particle, which denotes a single entity or solution of a huge problem; Swarm, which denotes any problem that is computationally very expensive and cannot be solved without optimization; and Optimization, which marks the finding of a best solution for a given problem. In the last stage, classification, the finalized selected features are classified and tested. In the proposed model, the features learned by the CNN are taken out of the last pooling layer to prevent the Softmax layer from classifying them. These features are optimized using PSO. The selected features are then passed onto the classification learner where they are tested and classified using various classifiers.

E. Post Processing

Post processing is the process before graphical interface creation in which the trained model which is enhanced through PSO are stored locally using serialization technique which can be used on the prior of the Graphical user interface. On the data or feature level, in the proposed method processing post the training or evaluation is not performed. But at the framework level, the trained model is stored as serialized binary object in the post-processing stage for its usage in the GUI level.

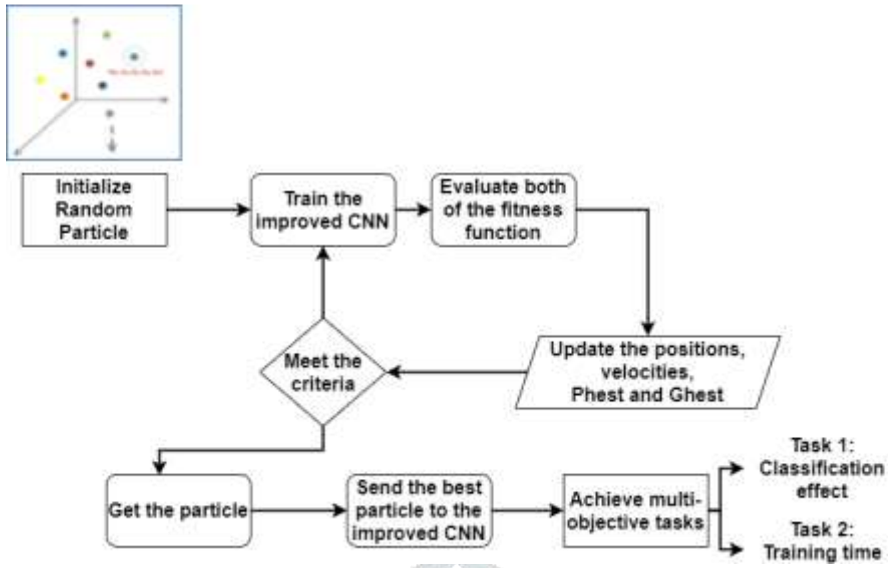
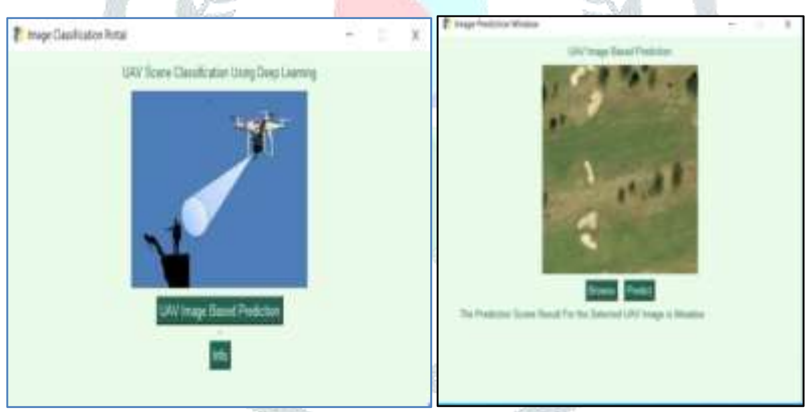


Figure 7. The flowchart of PSO that optimizes CNN

E. GUI Based Classification

In this section, the GUI created for the usage of the proposed model is depicted. The saved P-CNN model from the post processing stage is given as input for prediction. The user is allowed to browse images. The images should be re-sized to 256*256 before giving it as input as it is the mandate size governed during the course of the pre-processing in the proposed system.After the predict button is pressed the image is classified to the required class. The P-CNN is effective for wide range of classes as resulting to the contribution initially discussed regard to multi-label classification. Figure 8 (a) shows the front end of prediction and Figure 8 (b) shows the predicted class for browsed image.



(a) (b)

Figure8 (a): GUI for P-CNN model for image prediction (b): Predicted image from P-CNN model

IV.EXPERIMENTS AND RESULTS

In this section, the result and analysis of the proposed CNN model with descriptive information over the data set considered for the experimentation is depicted.

A. **Dataset Description:**

For this work, we have used two datasets. First the UC Merced (UCM) Land Use Dataset and the second WHU-RS Dataset, both of which are open access datasets. The first one was compiled by extracting successive frames from different videos of ski areas captured by UAVs freely available on the web. This dataset has a total of 100 frames. Resolution of the images is 256 x 256. The WHU-RS dataset consist of 950 images with source size of 600x600. The number of classes in the UCM is found to be 21 as that of WHU-RS is 19. Table 1 contains the specification of the data set considered in the proposed framework. Sample Images of the both datasets are shown in figure 9 (a) and (b) respectively.

Table 1: Dataset Details

Parameter	UCM dataset	WHU-RS dataset
Types	21	19
No of images	100	950
Pixel size	256*256	600*600

(a) (b)

Figure 9. (a): Sample Images from the UCM Dataset (b) Sample Images from the WHU-RS Dataset

B. Setup

As explained earlier, since our dataset is small and objects of interest are among the different classes onto which P-CNN- is trained, we have used the image processing algorithm as a feature extractor. Moreover, for optimal selection of the features for training and tuning PSO is employed. For this purpose, we removed the pooling layer of the network. A forward propagation of zero center normalized image of size 256x256 through the network outputs a vector of image descriptor elements. The research is implemented using python programming language on windows operating system assisted personal computer with 8GB physical RAM without any GPU support which marks the advantage of the computational redundancy and complexity.

V. Result Analysis

Figure 10 shows the performance of the PCNN approach in comparison to several pre-trained CNN models. The improved classifier accuracy demonstrates the effectiveness of pre-trained CNNs in classifying scene datasets. The researchers employed two datasets.MLP does not fare well with Image classification because spatial information is lost. SVM choosing kernel could be a problem for all kind of data these findings demonstrated that the suggested model produces superior classification results when applied to the datasets in question. All previous strategies are outperformed by the proposed model. The P-CNN method is significantly more accurate than other previously proposed methods.

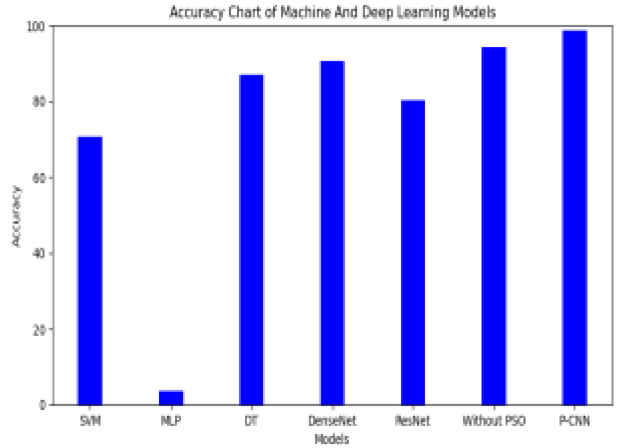


Figure 10.Bar chart showing the aaccuracy of PCNN model over different models.

VI. CONCLUSIONS

The identification of scenes from remote sensing images was very complex task with older techniques. The introduction of UAV open ups the new technology for capturing images from less height. Several methodologies for processing and classification objects and scenes from image captured by UAV are discussed in literature review. This proposed system takes a different analysis and detection approach for eliminating the issues happens to the older methods. The high-quality spatial image with high resolution acquired by the UAV contains huge amount of information which helps for better prediction of scenes. The classification issues are solved by implementing PSO and CNN techniques as a combination. And, to some extent, classification efficiency has improved in a short period of time, with a number of problems in scene classification successfully overcome to attain high accuracy. The extra steps taken in the pre-processing phase makes an impact on system performance. The machine learning model utilized two well-known datasets (UCM and WHU-RS) for training and testing. The performance analysis after testing shows that application of PCNN technique can achieve 98.7% accuracy compared to all the other methods. It proves that the model performs well than other models mentioned in the literature review. The integration of GUI with the system improves the reliability and usability of the system. In future, the dataset size is to be increased for increasing training accuracy. Multiple algorithm implementations in a combined form also can bring more effectiveness in scene classification.

References

[1] E. S. Márquez and A. V. Soto, "Cadastral stereo plotting production from unmmaned aerial vehicles imagery," 2017 First IEEE International Symposium of Geoscience and Remote Sensing (GRSS-CHILE), Valdivia, 2017, pp. 1-9.

[2] M. Nagai, T. Chen, R. Shibasaki, H. Kumagai and A. Ahmed, "UAV-Borne 3-D Mapping System by Multisensor Integration," in IEEE Transactions on Geoscience and Remote Sensing, vol. 47, no. 3, pp. 701-708, March 2009.

[3] L. Zhang, M. Hu, G. Wang and H. Wang, "Range-Dependent Map-Drift Algorithm for Focusing UAV SAR Imagery," in IEEE Geoscience and Remote Sensing Letters, vol. 13, no. 8, pp. 1158-1162, Aug. 2016.

[4] J. H. Kim, J. w. Kwon and J. Seo, "Multi-UAV-based stereo vision system without GPS for ground obstacle mapping to assist path planning of UGV," in Electronics Letters, vol. 50, no. 20, pp. 1431-1432, September 25 2014.

[5] K. J. Wu, T. S. Gregory, J. Moore, B. Hooper, D. Lewis and Z. T. H. Tse, "Development of an indoor guidance system for unmanned aerial vehicles with power industry applications," in IET Radar, Sonar & Navigation, vol. 11, no. 1, pp. 212-218, 1 2017.

[6] X. Li, Q. Yang, Z. Chen, X. Luo and W. Yan, "Visible defects detection based on UAV-based inspection in large-scale photovoltaic systems," in IET Renewable Power Generation, vol. 11, no. 10, pp. 1234-1244, 8 16 2017.

[7] L. R. Pinto, A. Moreira, L. Almeida and A. Rowe, "Characterizing Multihop Aerial Networks of COTS Multirotors," in IEEE Transactions on Industrial Informatics, vol. 13, no. 2, pp. 898-906, April 2017.

[8] P. Rudol and P. Doherty, "Human Body Detection and Geolocalization for UAV Search and Rescue Missions Using Color and Thermal Imagery," 2008 IEEE Aerospace Conference, Big Sky, MT, 2008, pp. 1-8.

[9] S. Verykokou, A. Doulamis, G. Athanasiou, C. Ioannidis and A. Amditis, "UAV-based 3D modelling of disaster scenes for Urban Search and Rescue," 2016 IEEE International Conference on Imaging Systems and Techniques (IST), Chania, 2016, pp. 106-111.

[10] A. Imdoukh, A. Shaker, A. Al-Toukhy, D. Kablaoui and M. El-Abd, "Semi-autonomous indoor firefighting UAV," 2017 18th International Conference on Advanced Robotics (ICAR), Hong Kong, 2017, pp. 310-315.

[11] Jing Liang, Pengshuai Li, Hui Zhao, Lu Han, Mingliang Qu, "Forest Species Classification of UAV Hyperspectral Image Using Deep Learning", Chinese Automation Congress (CAC), January 2021.

[12] Aghila Rajagopal, A. Ramachandran, K. Shankar , Manju Khari , Sudan Jha , Yongju Lee,And Gyanendra Prasad Joshi, "Fine-Tuned Residual Network-Based Features With Latent Variable Support Vector Machine-Based Optimal Scene Classification Model for Unmanned Aerial Vehicles", IEEE Access, Vol. 8, pp. 118396 - 118404, 2020.

[13] Christos Kyrkou, Theocharis Theocharides, "EmergencyNet: Efficient Aerial Image Classification for Drone-Based Emergency Monitoring Using Atrous Convolutional Feature Fusion", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 13, pp. 1687 - 1699, 2020.

[14] Leila Hashemi-Beni and Asmamaw A. Gebrehiwot, "Flood Extent Mapping: An Integrated Method Using Deep Learning and Region Growing Using UAV Optical Data", IEEE Journal Of Selected Topics In Applied Earth Observations And Remote Sensing, Vol. 14, 2021.

[15] Baojia Du, Dehua Mao, Zongming Wang, Zhiqiang Qiu, Hengqi Yan, Kaidong Feng, and Zhongbin Zhang, "Mapping Wetland Plant Communities Using Unmanned Aerial Vehicle Hyperspectral Imagery by Comparing Object/pixel-based Classifications Combining Multiple Machine-learning Algorithms", IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 14, pp. 8249 - 8258, 2021.

[16] Manjit Hota, Sudarshan Rao B , and Uttam Kumar, "Power Lines Detection And Segmentation In Multi-Spectral Uav Images Using Convolutional Neural Network", IEEE India Geoscience and Remote Sensing Symposium (InGARSS), Dec 2020.

[17] Marks Melo Moura, Luiz Eduardo Soares de Oliveira, Carlos Roberto Sanquetta, Alexis Bastos, Midhun Mohan and Ana Paula Dalla Corte, "Towards Amazon Forest Restoration: Automatic Detection of Species from UAV Imagery", Remote Sensing, Vol. 13, 2021.

[18] Bilel Benjdira, Taha Khursheed, Anis Koubaa, Adel Ammar, Kais Ouni, "Car Detection using Unmanned Aerial Vehicles: Comparison between Faster R-CNN and YOLOv3", 1st International Conference on Unmanned Vehicle Systems-Oman (UVS), March 2019.

[19] Shuang Zhang, Xuming Zhang, Aizhu Zhang, Hang Fu, Ji Cheng, Hui Huang, Genyun Sun, Li Zhang, Yanjuan Yao, "Fusion Of Low- And High- Level Features For Uav Hyperspectral Image Classification", 10th Workshop on Hyperspectral Imaging and Signal Processing: Evolution in Remote Sensing (WHISPERS), September 2019.

[20] Aghila Rajagopal, Gyanendra Prasad Joshi, A. Ramachandran, R.T. Subhalakshmi, Manju Khari, Sudan Jha, K. Shankar and Jinsang You, "A Deep Learning Model Based on Multi-Objective Particle Swarm Optimization for Scene Classification in Unmanned Aerial Vehicles", IEEE Access, Vol. 8, pp. 135383 - 135393, 2020.

[21] Lihong Su, Yuxia Huang, Zhiyong Hu, "An Empirical Study On Fully Convolutional Network And Hypercolumn Methods For Uav Remote Sensing Imagery Classification", IEEE International Geoscience and Remote Sensing Symposium, 2020.

[22] Giovanna Castellano, Ciro Castiello, Corrado Mencar And Gennaro Vessio, “Crowd Detection in Aerial Images using Spatial Graphs and Fully-Convolutional Neural Networks”, IEEE Access , Vol. 8, pp. 64534 - 64544, 2020.

[23] Ulzhalgas Seidaliyeva, Manal Alduraibi, Lyazzat Ilipbayeva, Nurzhigit Smailov, “Deep residual neural network-based classification of loaded and unloaded UAV images”, Fourth IEEE International Conference on Robotic Computing (IRC), Nov 2020.

[24] Rong Xiao , Yuze Wang, and Chao Tao, "Fine-Grained Road Scene Understanding From Aerial Images Based on Semisupervised Semantic Segmentation Networks", IEEE Geoscience and Remote Sensing Letters , pp. 1-5, March 2021.

[25] T. Moranduzzo and F. Melgani, "Detecting Cars in UAV Images With a Catalog-Based Approach," IEEE Transactions on Geoscience and Remote Sensing, vol. 52, no. 10, pp. 6356- 6367, Oct. 2014.

[26] K. Liu and G. Mattyus, "Fast Multiclass Vehicle Detection on Aerial Images," IEEE Geoscience and Remote Sensing Letters, vol. 12, no. 9, pp. 1938-1942, Sept. 2015.

[27] S. Kamate, N. Yilmazer, "Application of Object Detection and Tracking Techniques for Unmanned Aerial Vehicles", in Procedia Computer Science, vol.61, pp. 436-441, 2015.

[28] Popescu, Dan, and Loretta Ichim. "Image Recognition in UAV Application Based on Texture Analysis." in Proc. International Conference on Advanced Concepts for Intelligent Vision Systems, pp. 693-704. Springer International Publishing, 2015

[29] Deng, J.; Dong, W.; Socher, R.; Li, L.-J.; Li, K.; Fei-Fei, L. Imagenet: A large-scale hierarchical image database. In Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on; IEEE, 2009; pp. 248–255.

[30] Sharif Razavian, A.; Azizpour, H.; Sullivan, J.; Carlsson, S. CNN features off-the-shelf: an astounding baseline for recognition. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops; 2014; pp. 806–813.

[31] Donahue, J.; Jia, Y.; Vinyals, O.; Hoffman, J.; Zhang, N.; Tzeng, E.; Darrell, T. DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition. In ICML; 2014; pp. 647–655.

[32] O'Shea, K.; Nash, R. An Introduction to Convolutional Neural Networks. ArXiv Prepr. ArXiv151108458 2015.

[33] Nair, V.; Hinton, G. E. Rectified linear units improve restricted boltzmann machines. In Proceedings of the 27th International Conference on Machine Learning (ICML-10); 2010; pp. 807–814.

Mrs. Reshma M is working as a Lecturer, Department of Computer Science and Engineering, Government Polytechnic Immadihalli, DTE, Bengaluru. She is pursuing M.Tech in computer science branch from UVCE, Bangalore. She completed B.E at New Horizon college of Engineering, Bangalore. Her research interests are in the field of Image Processing, Machine and Deep learning.

Dr. Manjula S H is currently working as a Professor, Department of Computer Science and Engineering, UVCE, Bangalore University, Bengaluru. She is a member of the Academic Senate, VTU Belagavi. She obtained BE and ME in the Department of Computer Science and Engineering from UVCE, Bengaluru.Ph.D.in Computer Science and Engineering, Chennai. She has published 120 technical articles in refereed journals and international conferences and authored three books. Her research interests are in the field of IoT, Cloud Computing, Wireless Sensor Networks and data mining, AI and Machine Learning.