IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

MACHINE LEARNING-DRIVEN AIRPORT DETECTION IN OPTICAL SATELLITE IMAGERY FOR TRANSPORTATION USING CNN

Monika Manoharrao Gawande, Dr. Ravindra M. Deshmukh
Master's Student, Professor
Department of Electronics & Telecommunication Engineering,
Dr. Rajendra Gode Institute of Technology & Research, Sant Gadge Baba Amravati University, Amravati, India

Abstract*:* Fast and automatic detection of airports from remote sensing images is useful for many military and civilian applications. In this paper, a fast automatic detection method is proposed to detect airports from remote sensing images based on convolutional neural networks algorithm. This method first applies a convolutional neural network to generate candidate airport regions. Based on the features extracted from these proposals, it then uses another convolutional neural network to perform airport detection. By taking the typical elongated linear geometric shape of airports into consideration, some specific improvements to the method are proposed. These approaches successfully improve the quality of positive samples and achieve a better accuracy in the final detection results. Experimental results on an airport dataset, Landsat 8 images, and a Gaofen-1 satellite scene demonstrate the effectiveness and efficiency of the proposed method.

***Index Terms* -** Airport detection; Convolutional Neural Network.

1. INTRODUCATION

Airports are important structures from both economic and military perspective. Economically, as fundamental cargo and passenger transportation stations, airports serve to attract and retain businesses with national and global ties. Therefore, air- ports are a major force in the local, regional, national and global economy, becoming increasingly significant in terms of financial reasons.

The military airports, i.e. airbases, are also critical strategic targets considering the importance of the aviation branch of a nation's defense forces. Airbases are used for not only take-off and landing of crucial bomber and fighter units, but also conse- quential support operations such as strategic and tactical airlift, combat airdrop and medical evacuation, promoting the worth of airports. From this point of view, automatic detection of airports can provide vital intelligence to take well-timed military measures in a state of war.

The technological improvements on both computational hardware and pattern recognition techniques made identification of airports an attainable objective. Besides, increasing number of countries that have their own satellites renders the problem even more attractive, by the supplied unbiased data to investigate.

2. PROPOSED DETECTION ALGORITHM

In the machine learning area, CNNs have demonstrated a much better feature representation than traditional methods [21] and they have shown great potential in many visual applications. A CNN is formed by a stack of distinct layers, where each successive layer uses the output from the previous layer as input. These multiple layers make the network very expressive to learn relationships between inputs and outputs. By using an appropriate loss function on a set of labeled training data, which penalizes the deviation between the predicted and true labels, the weights of these layers can be obtained by supervised learning. In the following, we first introduce the network architecture of the proposed method for airport detection, and then present some specific improvement techniques of the proposed method. The flowchart of the proposed algorithm is shown in Figure.

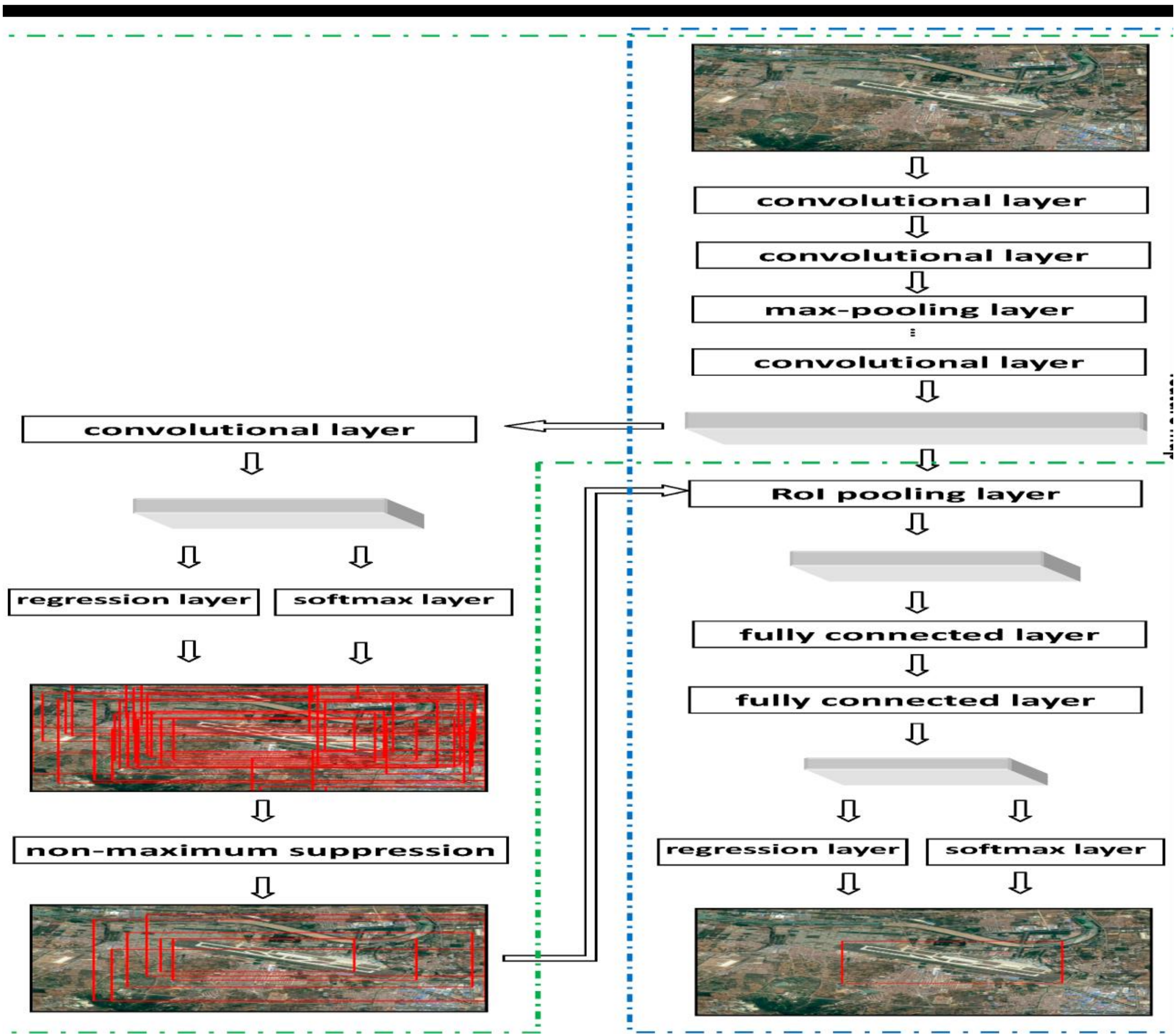

Fig a. The Flowchart of the proposed algorithm

The proposed runway detection method basically consists of two main stages, which are binary classification of regions based on textural properties, and analysis of these regions based on shape. In the first stage a coarse segmentation is done on the satellite image, in order to find candidate regions for airport runway, based on the textural properties. This segmentation is a binary segmentation, where regions are labeled as either “probably belongs to a runway” or “probably does not belong to a runway”. After this segmentation, only regions that possibly belong to a runway are considered and proceed to the second stage. In the second stage, a shape detection algorithm, which discovers long parallel line segments, is carried out on the “possibly runway” regions. These long parallel lines are considered as the identification marks of the two long sides of the elongated rectangle shape of the runway.

3. DATASET

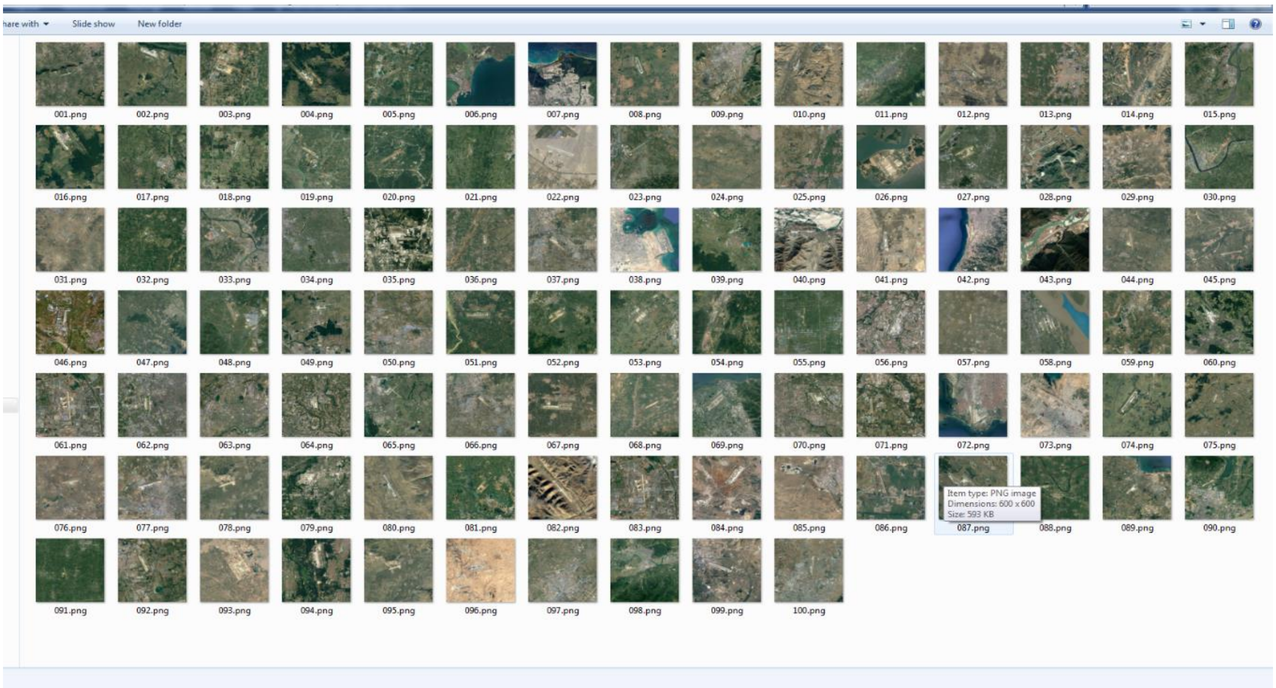

Fig b. Dataset of 100 RSI

4. EXPERIMENTAL RESULTS

In this chapter, the experimental results obtained by running the proposed algorithm are given. These experimental results are carried out with a dataset, consisting of 78, large satellite images having sizes of 600 × 600 on average and resolution of 1 meter that are obtained using Google Earth software. 30 of these images are randomly selected for training of CNN and 48 of them are reserved for testing. Each image is divided into blocks of size 32 × 32 and in this way blocks are obtained for training. Each block of the training images is labeled as runway (positive) if more than half of its pixels belongs to main runway of an airport and labeled as non-runway (negative) if not.

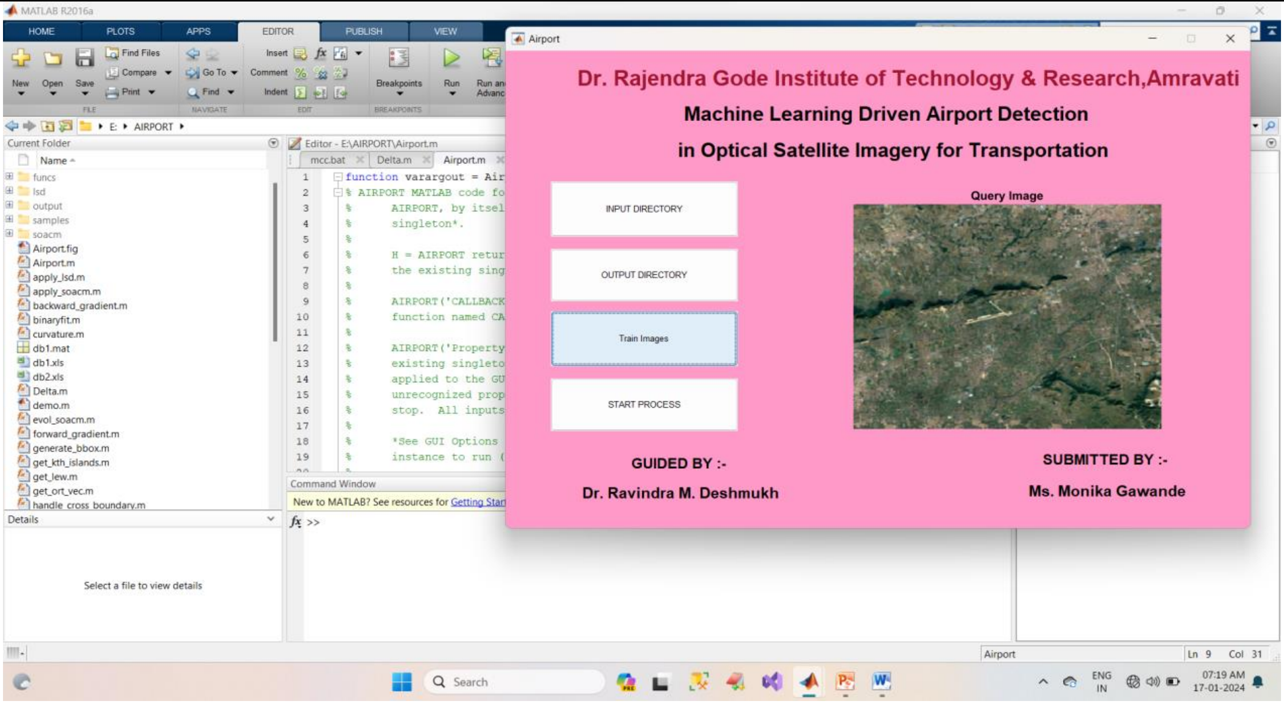

Fig c. GUI of Proposed Work

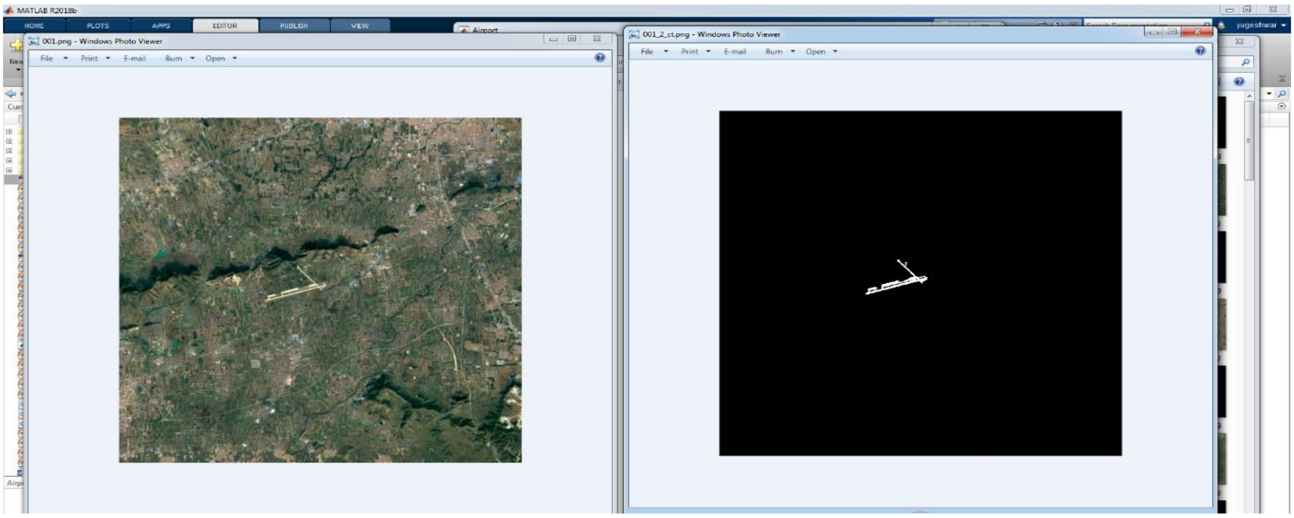

Fig d. Results of Proposed Work

5. CONCLUSION

Extracting all of the 100 features from a 600 x 600 image, takes approximately 115 minutes, where extracting the selected 26 unique features, which is the case for all of the images after training, takes 78 minutes by using this system. Keeping the size of the data and the platform in mind, algorithm performs fairly well. A performance improvement alternative is given in Section 5.1. It is also always possible to decide the number of features to be used with a trade off between performance and computation time, due to the scalability provided by CNN. After the training, all blocks of an image take approximately 5 seconds to be classified.

6. REFERENCES

1) M.F. Augusteijn, L.E. Clemens, and K.A. Shaw. Performance evaluation of tex- ture measures for ground cover identification in satellite images by means of a neural network classifier. *Geoscience and Remote Sensing, IEEE Transactions on*, 33(3):616–626, May 1995.
2) D. H. Ballard. Generalizing the hough transform to detect arbitrary shapes. *Readings in computer vision: issues, problems, principles, and paradigms*, pages 714–725, 1987.
3) Matjaz Bevk and Igor Kononenko. A statistical approach to texture description of medical images: A preliminary study. *Computer-Based Medical Systems, IEEE Symposium on*, 0:239, 2002.
4) **J** Canny. A computational approach to edge detection. *IEEE Trans. Pattern Anal. Mach. Intell.*, 8(6):679–698, 1986.
5) Russell G. Congalton and Kass Green. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Lewis Publishers, New York, NY, USA, 1999.
6) Richard O. Duda and Peter E. Hart. Use of hough transformation to detect lines and curves in pictures. *Commun. ACM*, 15(1):11 – 15, 1972.
7) C. Fernandez-Maloigne, D. Laugier, and A. Bekkhoucha. Texture analysis for road detection. In *Intelligent Vehicles '92 Symposium., Proceedings of the*, pages 219–224, Jun-1 Jul 1992.
8) Yoav Freund and Robert E. Schapire. A short introduction to boosting. In *In Proceedings of the Sixteenth International Joint Conference on Artificial Intelli-gence*, pages 1401–1406. Morgan Kaufmann, 1999.
9) Rafael C. Gonzalez and Richard E. Woods. *Digital Image Processing*. Addison- Wesley Longman Publishing Co., Inc., Boston, MA, USA, 2001.
10) Pranav Gupta and Anupam Agrawal. Airport detection in high-resolution panchromatic satellite images. *Journal of Institution of Engineers (India)*,88(5):3–9, 2007.
11) JunWei Han, Lei Guo, and YongSheng Bao. A method of automatic finding airport runways in aerial images. In *Signal Processing, 2002 6th International Conference on*, volume 1, pages 731–734 vol.1, Aug. 2002.
12) Robert M. Haralick, K. Shanmugam, and Its'Hak Dinstein. Textural features for image classification. *Systems, Man and Cybernetics, IEEE Transactions on*, 3(6):610–621, Nov. 1973.