Categorization Of Military And Passenger Aircraft Through Cnn For Security

[1]M.Ramya, [2]Dr.E.Thenmozhi, [3]K.Aditi, [4]G.Mahalakshmi, [5]R.Raveena
[1] Assistant Professor, [2]Associate Professor, Dept. Information Technology, Panimalar Institute of Technology, India.
[3,4,5] Student, Dept. Of Information Technology, Panimalar Institute of Technology, India.

Abstract: -In order to prevent unintended aeroplane mishaps, the proposed system analyses and categories the images to determine if they are military aircraft or passenger aircraft. Currently, the two vital purpose of aircrafts are civil and military. Private, commercial, and government-owned aircraft that primarily transport freight and people are considered civil aviation. State-owned aircraft used for transport, training, security, and defence are included in military aviation. One of the most crucial and tedious tasks in the realm of remote sensing is addressing aircraft, particularly for the busiest airways. To help the airport administration, military, and the related other industries, a contiguous deepening of artificial intelligence approach known as Convolutional Neural Network for aircraft recognition is used.

Keywords: Military, passenger aircraft, CNN

I. Introduction

As air crafts are of two types such as civilian and military air crafts, it is often difficult to differentiate between both which resulted in attacks and accidents of the passengers. This is due to the incorrect assumption of a passenger aircraft as a military aircraft of another countries. On the other side, the restricted war zones or boundaries remains unsafe to the particular region and the military due to the incoming of anonymous flights. To solve all these problems, a deep learning method called CNN is utilized by taking two predefined models such as AlexNet, LeNet and a user defined architecture model named UserNet inorder to classify whether it is a passenger aircraft or military aircraft using image classification. Different parameters are taken into account to train the machine to predict the differences between both .This in turn helps the air traffic controller to solve the chaos and prevent mis happenings by communicating through the transponders

II. Literature Survey

[1] An Adaptive Framework for Optimization and Prediction of Air Traffic Management (Sub-)Systems with Machine Learning by Stefan Reitmann, and Michael Schultz in 2022 with gradatim framework is furnished in arithmetical modelling .Baseline data for the application region is dependent for authenticating on real statistics[1].

[2] Aircraft Detection for Remote Sensing Image Based on Bidirectional and Dense Feature Fusion by Liming Zhou , Haoxin Yan in 2021 to enhance the observation in accuracy and fall off in missed discernment YOLOv3 object discernment algorithm is not better than network[2].

[3] A Multi-Dimensional Goal Aircraft Guidance Approach Based on Reinforcement Learning with a Reward Shaping Algorithm by Wenqiang Zu , Hongyu Yang in 2021 it provides solution in solving multi goal decision making in aircraft gideance but It is unpleasant in frequency changes[3].

[4] SCAN: Scattering Characteristics Analysis Network for Few-Shot Aircraft Classification in High-Resolution SAR Images by Xian Sun , Yixuan Lv , Zhirui Wang and Kun Fu in 2022 for solving few shot classification problems in SAR domain for that framework SCAN is proposed . Experimental conclusion are being used to determine the rationality of the proposed process[4].

III. Existing System

Introducing the scattering characteristics analysis network, an unique few-shot learning framework (SCAN). First, a scattering extraction module (SEM) is created to integrate the target imaging mechanism with the network, which uses explicit supervision to learn the quantity and distribution of scattering points for each type of target. For the tests, a new dataset called the SAR aircraft categorization dataset is also created. Second, ASC was created to address the issue brought on by the SAR imaging results' susceptibility to TAAs. Lastly, we utilize the suggested FEM to make use of frequency-domain data. SAR-ACD experiments show that the suggested technique is valid. For 5-way 1-shots, the model's performance has improved by 4.8%. The drawbacks include the fact that VGG and Resnet were not used as classifiers in earlier research.

IV. Proposed System

Convolutional neural networks (CNNs) is a modern and reliable machine learning model that the proposed system uses to automatically categorise the identification of military aircraft. For each class of input photographs that was classified, various aircraft images were gathered. The Convolutional Neural Network is the DL technique employed in the study (CNN). If the CNN approach is supported by the successful identification of military aircraft and addition of additional feature extraction methods, it is projected that the success of the results acquired would grow. This approach is deployed by displaying the prediction results in a local Django web application. The CNN algorithm has the benefit of being simple. There are more architectures compared. Django was used to deploy.

V. Architecture Diagram

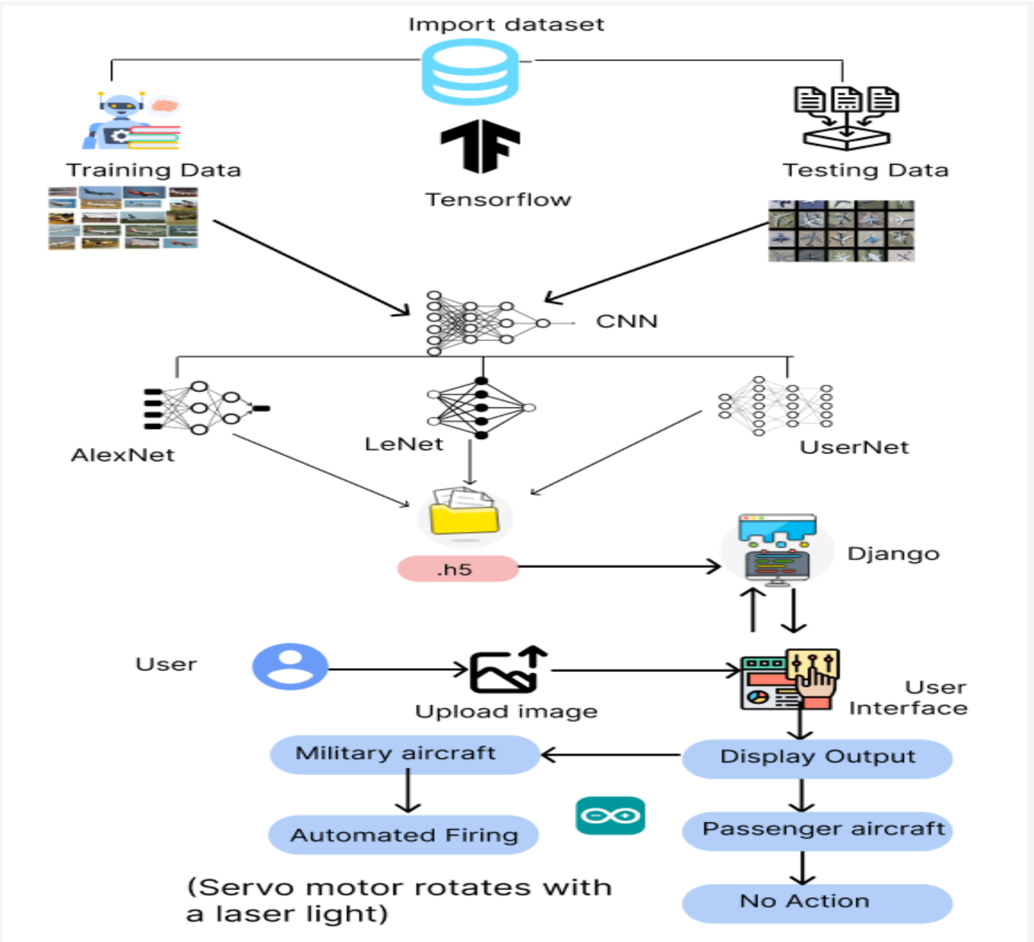

Fig.1.Architecture diagram

The overall working of the project is as follows: First the data set is imported which contains the images of the military and passenger aircraft images for training and testing. There by, we feed the input to

three different architectures of CNN namely AlexNet, LeNet which are predefined and UserNet which is a user defined architecture model. As a result, the architecture which produces better accuracy among the three is integrated with the user interface using django framework. The user uploads the image of aircraft and obtain the result as military or passenger aircraft. If it is a military aircraft, the LCD in arduino displays and the servo motor rotates with the laser light on that depicts automated firing of illegal aircrafts.

VI. Algorithm Description

A CNN stands for Convolutional Neural Network, which is a type of neural network that is commonly used in image recognition, computer vision, and natural language processing. CNNs are particularly effective in image processing tasks because they can automatically learn and extract meaningful features from the images.

Overview of how a CNN works:

Input Layer: The input layer of the CNN takes in the raw image data. Each pixel in the image is represented by a numerical value, and the input layer is typically a 3D array of pixels (height x width x color channels).

Convolutional Layer: The first layer in a CNN is typically a convolutional layer. The purpose of this layer is to extract features from the input image. The layer consists of a set of filters or kernels that slide over the input image, performing a convolution operation that produces a feature map. Each filter extracts a different type of feature, such as edges, corners, or blobs.

ReLU Layer: After the convolutional layer, a Rectified Linear Unit (ReLU) layer is applied to the feature map. This layer introduces non-linearity to the network by applying the ReLU activation function to each pixel in the feature map. The ReLU function sets all negative values to zero, while leaving positive values unchanged.

Pooling Layer: Reduces the size of the feature map, while retaining the most important information. The most common pooling operation is max pooling, which involves dividing the feature map into non-overlapping regions and taking the maximum value within each region. This reduces the spatial resolution of the feature map, while retaining the most important features.

Convolutional and ReLU Layers: The previous steps of convolution, ReLU, and pooling are repeated several times to extract more complex and abstract features from the image.

Flatten Layer: After several convolutional layers, the feature map is flattened into a 1D array. This allows the network to make predictions based on the extracted features.

Fully Connected Layer: The flattened feature map is passed through a fully connected layer, which is similar to a traditional neural network layer. The fully connected layer performs a linear transformation of the input, followed by a non-linear activation function.

Output Layer: The final layer in a CNN is typically a softmax layer, which produces a probability distribution over the possible output classes. The class with the highest probability is taken as the predicted class.

VII. Modules Of The Project

UserNet

IMPORT THE GIVEN IMAGE FROM DATASET:

Import the image dataset using the Keras preprocessing image data generator function. Set the train, test, and validation datasets, target size, batch size, and class-mode from the data generator function.

TO TRAIN THE MODULE BY GIVEN IMAGE DATASET:

Train the dataset using a classifier and fit generator function by adding layers of CNN. We make training steps per epoch, then total number of epochs, validation data and validation steps using this data we can train our dataset.

AlexNet:

The design of AlexNet comprises of

- 5 convolutional layers,
- 3 max-pooling layers,
- 2 normalization layers,
- 2 fully connected layers, and
- 1 softmax layer.

Input Layer: The input layer of AlexNet takes in a 227x227 RGB image.

The first convolutional layer filters the input image with a 11x11 kernel size, followed by a ReLU activation function and a max-pooling layer. The second convolutional layer filters the output from the first layer with a 5x5 kernel size, followed by a ReLU activation function and a max-pooling layer. The third, fourth, and fifth convolutional layers have the same structure as the second layer.

After the five convolutional layers, AlexNet has three fully connected layers. The first two fully connected layers have 4,096 neurons each, and the third fully connected layer has 1,000 neurons (corresponding to the 1,000 classes in the ImageNet dataset). Then followed by a ReLU activation function, except for the last one, which is followed by a softmax function to generate the class probabilities.

To be precise, AlexNet takes an input image and passes it through several convolutional and pooling layers, followed by several fully connected layers, in order to provide a probability distribution over output classes.

LeNet:

LeNet is a compact deep learning network that consists of fundamental modules such as convolutional layer, pooling layer, and fully connected layer. It serves as a cornerstone for other deep learning models. LeNet5 improves our comprehension of the convolutional layer and pooling layer via example analysis.

Convolutional Layers: The input image is convolved with learnable filters in the convolutional layer to extract features. The output is a feature map. In your project, the features extracted could include the shape, size, and features unique to military or passenger aircraft.

Pooling Layers: The feature map is down-sampled by pooling the maximum value from each window in the pooling layer. The output is a pooled feature map with reduced dimensions. This helps to avoid over-fitting and makes the model computationally efficient.

Fully Connected Layers: The pooled feature map is flattened and fed to the fully connected layer. This layer learns to map the features to a set of output classes. In your project, the output classes could be military aircraft or passenger aircraft.

Softmax Layer: The output of the fully connected layer is passed through a softmax function to obtain the class probabilities. The predicted class is the one with the highest probability.

Deploy

Deploying the model in Django Framework and classifying output

This module converts the trained deep learning model to a hierarchical data format file (.h5 file). followed by deploying the model in Django Framework to provide a better user interface. Finally, classify the output using the deployed model.

VIII. Block Diagram

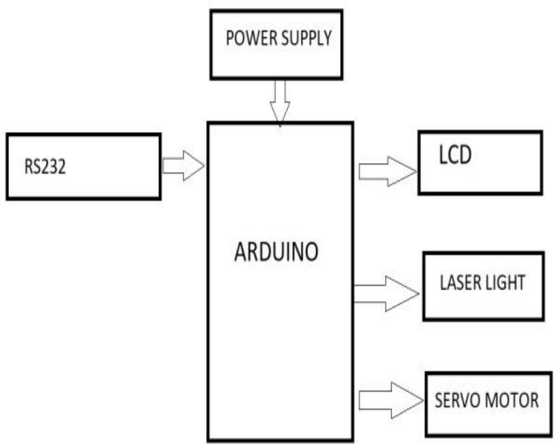

Fig.2. Block diagram

A hardware setup is attached which contains an Arduino connected to the LCD, laser light and a servo motor. A RS232 cable is used to connect the hardware and software. A power supply wire is also connected in order to make the Arduino work. Here, when the result shows as a passenger aircraft, no action takes place except for the display in the LCD as passenger aircraft. But if the result is a military aircraft, then the servo motor that is attached with the laser light blinks and rotates for about 180 degeree portraying the action of automated firing of the illegal military air crafts that enters the restricted area.

IX. Implementation

The user interface integrated with django framework is used to get the input from the user as a image.

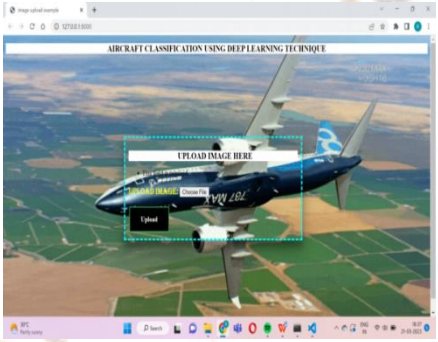

Fig.3.Screenshot1

Once the image is uploaded from the test data set, click on the result button to obtain the classification output.

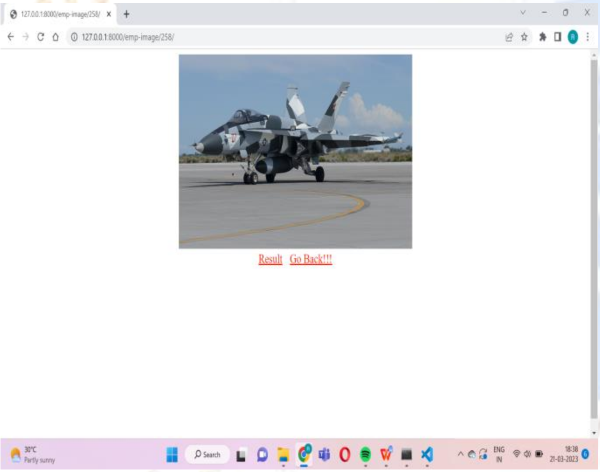

Fig.4 Screenshot2

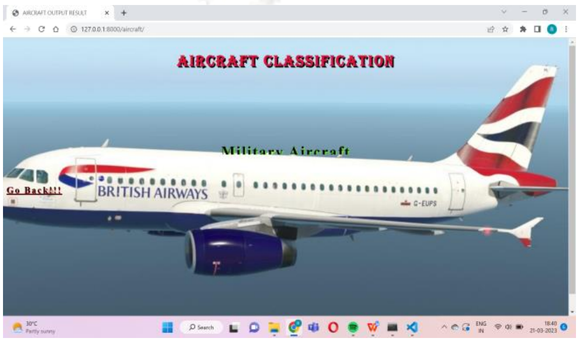

Fig.5.Screenshot3

Once the result is displayed as military aircraft , the LCD displays the same in the Arduino setup and the servo motor rotates with the laser light which depicts the mechanism of automated firing.

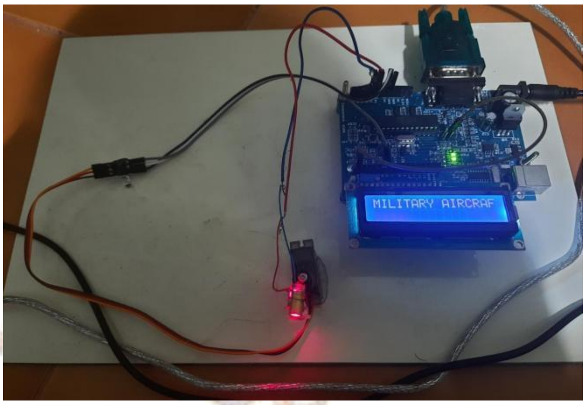

Fig.6. Output

X.CONCLUSION

In proposed system, a research to classify military aircraft or passenger aircraft images using deep learning techniques was developed. This is a complex problem that has already been approached several times with different techniques. While good results have been achieved using feature engineering, this project focused on feature learning, which is one of DL promises. While feature engineering is not necessary, image pre-processing boosts classification accuracy. Hence, it reduces noise on the input data. Nowadays, military aircraft or passenger aircraft detection software includes the use of feature engineering. A solution totally based on feature learning does not seem close yet because of a major limitation. This, military aircraft or passenger aircraft classification could be achieved by means of deep learning techniques.

XI. FUTURE WORK

Following these guidelines will help the network's accuracy and generalisation further improve. The foremost suggestion is to make use of the entire dataset while optimizing. The most aptable methology to implement is the batch optimization huge datasets. The other method is to evaluate military aircraft or passenger aircraft one by one. This can lead to detect military aircraft or passenger aircraft which are very tedious to categorize. Finally, using a larger dataset for training seems beneficial. However, such a dataset might not exist nowadays. Using several datasets might be a solution, but a careful procedure to normalize them is required. Finally, using full dataset for training, pre-training on each military aircraft and passenger aircraft and using a larger dataset seem to have the possibility to improve the network’s performance. Thus, they should be addressed in future research on this topic.

XII. REFERENCES

1. Reitmann, Stefan & Schultz, Michael. (2022). An Adaptive Framework for Optimization and Prediction of Air Traffic Management (Sub-)Systems with Machine Learning. Aerospace. 9. 77. 10.3390/aerospace9020077.

2. Zhou, Liming & Yan, Haoxin & Shan, Yingzi & Zheng, Chang & Liu, Yang & Zuo, Xianyu & Qiao, Baojun. (2021). Aircraft Detection for Remote Sensing Images Based on Deep Convolutional Neural Networks. Journal of Electrical and Computer Engineering. 2021. 1-16. 10.1155/2021/4685644.

3. Zu, Wenqiang & Yang, Hongyu & Liu, Renyu & Ji, Yulong. (2021). A Multi-Dimensional Goal Aircraft Guidance Approach Based on Reinforcement Learning with a Reward Shaping Algorithm. Sensors. 21. 5643. 10.3390/s21165643.

4. Sun, Xian & Lv, Yixuan & Wang, Zhirui & Fu, Kun. (2022). SCAN: Scattering Characteristics Analysis Network for Few-Shot Aircraft Classification in High- Resolution SAR Images. IEEE Transactions on Geoscience and Remote Sensing. 60. 1-1. 10.1109/TGRS.2022.3166174.

5. Statistics, & Stat, & Youssef, Youssef & Merrouchi, Mohamed & Abdelmounim, Elhassane & Gadi, Taoufiq. (2022). Classification of Aircraft in Remote Sensing Images Based on Deep Convolutional Neural Networks. Statistics Optimization & Information Computing. 10. 4-11. 10.19139/soic-2310-5070-1143.

6. Fu, Kun & Dai, Wei & Zhang, Yue & Wang, Zhirui & Yan, Menglong & Sun, Xian. (2019). MultiCAM: Multiple Class Activation Mapping for Aircraft Recognition in Remote Sensing Images. Remote Sensing. 11. 544. 10.3390/rs11050544.

7. Zhang, Yuhang & Sun, Hao & Zuo, Jiawei & Wang, Hongqi & Xu, Guangluan & Sun, Xian. (2018). Aircraft Type Recognition in Remote Sensing Images Based on Feature Learning with Conditional Generative Adversarial Networks. Remote Sensing. 10. 1123. 10.3390/rs10071123.

8. Zuo, Jiawei & Xu, Guangluan & Fu, Kun & Sun, Xian & Sun, Hao. (2018). Aircraft Type Recognition Based on Segmentation With Deep Convolutional Neural Networks. IEEE Geoscience and Remote Sensing Letters. PP. 1-5. 10.1109/LGRS.2017.2786232.

9. Huang, Xiaolan & Xu, Kai & Huang, Chuming & Wang, Chengrui & Qin, Kun. (2021). Multiple Instance Learning Convolutional Neural Networks for Fine-Grained Aircraft Recognition. Remote Sensing. 13. 5132. 10.3390/rs13245132.

10. Xiong, Yunsheng & Niu, Xin & Dou, Yong & Qie, Hang & Wang, Kang. (2020). Non-locally Enhanced Feature Fusion Network for Aircraft Recognition in Remote Sensing Images. Remote Sensing. 12. 681. 10.3390/rs12040681.

11. Wu, Qichang & Sun, Hao & Sun, Xian & Zhang, Daobing & Fu, Kun & Wang, Hongqi. (2015). Aircraft Recognition in High-Resolution Optical Satellite Remote Sensing Images. Geoscience and Remote Sensing Letters, IEEE. 12. 112-116. 10.1109/LGRS.2014.2328358.

12. Zhao, Baojun & Tang, Wei & Pan, Yu & Han, Yuqi & Wang, Wenzheng. (2021). Aircraft Type Recognition in Remote Sensing Images: Bilinear Discriminative Extreme Learning Machine Framework. Electronics. 10. 2046. 10.3390/electronics10172046.

13. Gao, Yilin-Kyle & He, Hongjie & Lu, Dening & Xu, Linlin & Ma, Lingfei & Li, Jonathan. (2022). Optimizing and Evaluating Swin Transformer for Aircraft Classification: Analysis and Generalizability of the MTARSI Dataset. PP. 1-1. 10.1109/ACCESS.2022.3231327.

14. Azam, Faisal & Rizvi, Akash & Khan, Wazir & Aalsalem, Mohammed & Yu, Heejung & Zikria, Yousaf. (2021). Aircraft Classification Based on PCA and Feature Fusion Techniques in Convolutional Neural Network. IEEE Access. 9. 2169-3536. 10.1109/ACCESS.2021.3132062.

15. Steininger, Daniel & Widhalm, Verena & Simon, Julia & Kriegler, Andreas & Sulzbacher, Christoph. (2021). The Aircraft Context Dataset: Understanding and Optimizing Data Variability in Aerial Domains. 10.1109/ICCVW54120.2021.00426.

16. Shermeyer, Jacob & Hossler, Thomas & Etten, Adam & Hogan, Daniel & Lewis, Ryan & Kim, Daeil. (2021). RarePlanes: Synthetic Data Takes Flight. 207-217. 10.1109/WACV48630.2021.00025.

17. Tang, Wei & Deng, Chenwei & Han, Yuqi & Huang, Yun & Zhao, Baojun. (2020). SRARNet:A Unified Framework for Joint Superresolution and Aircraft Recognition. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing. PP. 1-1. 10.1109/JSTARS.2020.3037225.

18. Liang, Wei & Li, Jihao & Wenhui, Diao & Sun, Xian & Fu, Kun & Wu, Yirong. (2020). FGATR-Net: Automatic Network Architecture Design for Fine-Grained Aircraft Type Recognition in Remote Sensing Images. Remote Sensing. 12. 4187. 10.3390/rs12244187.

19. Sumari, Arwin & Adinandra, Dimas & Rachmad Syulistyo, Arie & Lovrenčić, Sandra. (2022). Intelligent Military Aircraft Recognition and Identification to Support Military Personnel on the Air Observation Operation. International Journal on Advanced Science, Engineering and Information Technology. 12. 2571. 10.18517/ijaseit.12.6.16944.

20. Sumari, Arwin & Pranata, Aldi & Mashudi, Irsyad & Noer Syamsiana, Ika & Sereati, Catherine. (2022). Automatic Target Recognition and Identification for Military Ground-to-Air Observation Tasks using Support Vector Machine and Information Fusion. 01-08. 10.1109/ICISS55894.2022.9915256.

21. Szabadföldi, István. (2021). Artificial Intelligence in Military Application – Opportunities and Challenges. Land Forces Academy Review. 26. 157-165. 10.2478/raft-2021-0022.

22.Chen, L. & Zhou, L. & Liu, J.. (2020). Aircraft recognition from remote sensing images based on machine vision. Journal of Information Processing Systems. 16. 795-808. 10.3745/JIPS.02.0136.

23. JIANHUI, LIU & JIANG, GANGWU & Wang, Xin & Xu, Baiqi & Yu, Peidong. (2020). Feature Extraction and Identification of Military Aircraft Based on Remote Sensing Image. 128-133. 10.1145/3445815.3445837.

24. K. M. Hasib, N. A. Towhid and M. G. R. Alam, "OnlineReview based Sentiment Classification on Bangladesh Airline Service using Supervised Learning," 2021 5th International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), Dhaka, Bangladesh, 2021, pp. 1-6, doi: 10.1109/ICEEICT53905.2021.9667818.

25. Y. Dong, J. Tao, Y. Zhang, W. Lin and J. Ai, "Deep Learning in Aircraft Design, Dynamics, and Control: Review and Prospects," in IEEE Transactions on Aerospace and Electronic Systems, vol. 57, no. 4, pp. 2346-2368, Aug. 2021, doi: 10.1109/TAES.2021.3056086.

26. Zhou, Liming & Yan, Haoxin & Zheng, Chang & Rao, Xiaohan & Li, Yahui & Yang, Wencheng & Tian, Junfeng & Fan, Minghu & Zuo, Xianyu. (2021). Aircraft Detection for Remote Sensing Image Based on Bidirectional and Dense Feature Fusion. Computational Intelligence and Neuroscience. 2021. 1-14. 10.1155/2021/7618828.

27. Yanfeng Wang, Tao Wang, Xin Zhou, Weiwei Cai, Runmin Liu, Meigen Huang, Tian Jing, Mu Lin, Hua He, Weiping Wang, Yifan Zhu, "TransEffiDet: Aircraft Detection and Classification in Aerial Images Based on EfficientDet and Transformer", Computational Intelligence and Neuroscience, vol. 2022, Article ID 22625

28. Kang, Yuzhuo & Wang, Zhirui & Zuo, Haoyu & Zhang, Yidan & Yang, Zhujun & Sun, Xian & Fu, Kun. (2023). ST-Net: Scattering Topology Network for Aircraft Classification in High-Resolution SAR Images. IEEE Transactions on Geoscience and Remote Sensing. PP. 1-1. 10.1109/TGRS.2023.3236987.

29. Z. -H. Chen and J. -C. Juang, "Neural Network Learning to Identify Airport Runway Taxiway Numbers," 2018 International Symposium on Computer, Consumer and Control (IS3C), Taichung, Taiwan, 2018, pp. 153-157, doi: 10.1109/IS3C.2018.00046.

30. Liu, Hongwei & Zhong, Hanlu & Wu, Jiayuan & Cheng, Bo & Zhou, Zhengyu & Cao, Fanghua. (2023). The Research Status and Development of Military Aircraft Ground Support Equipment. 10.1007/978-981-19-7652- 0_62.

31. atratus, Coragyps & caerulescens, Chen & =, pelicans & phoeniceus, buteos & cyanocephalus, Euphagus & ater, Molothrus & vulgaris, Sturnus & =, horned & Hirundinidae, swallows & Apodidae, & hazard, bird–aircraft & model, bird-avoidance & birdstrike, & aura, Cathartes & aircraft, military & vulture, turkey. (2009). Ranking the risk of wildlife species hazardous to military aircraft. Wildlife Society Bulletin. 258-264. 10.2193/0091- 7648(2005)33[258:RTROWS]2.0.CO;2