A DEEP LEARNING APPROACH TO CLASSIFY DRONES AND BIRDS

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Abstract - *Drones are gaining popularity not just for recreational use, but also for various engineering, disaster management, logistics, and airport security applications. However, their potential use in malicious activities has raised concerns about physical infrastructure security, safety, and surveillance at airports. There have been several reports in recent years of unauthorized drone use causing disruptions in airline operations. To address this problem, a new deep learning-based method has been proposed in this study. This approach is efficient in detecting and recognizing two types of drones and birds, and it outperforms existing detection systems in the literature. The physical and behavioral similarities between drones and birds often lead to confusion, but the proposed method can not only detect the presence or absence of drones but also distinguish between different types of drones and differentiate them from birds.*

Key Words: drone; UAV; deep learning; convolutional neural network CNN; drone image dataset; drone detection; drone recognition.

1. INTRODUCTION

As drone manufacturing technologies continue to advance, their usage in military, commercial, and security settings is increasing. These unmanned aerial vehicles (UAVs) have become a popular choice for applications like airport security, facility protection, and integration into surveillance systems due to their effectiveness. However, drones can also pose a serious threat in security settings, making it important to develop efficient approaches to detect and identify them. This is especially crucial in areas like airport security and military systems, where the intrusion of drones could have dire consequences.

The detection, recognition, and identification of drones are essential to ensure public safety and mitigate the potential threats they pose. Detection involves observing the target and identifying any suspicious activity, while recognition involves categorizing the target. Identification refers to accurately diagnosing the type of target. While different sensors can be used to detect and recognize drones, visible imagery is preferred due to its high resolution, low cost, and compatibility with various drones.

However, using visible imagery also presents challenges like crowded backgrounds and confusing drones with birds, which requires a suitable method to solve. The YOLO Deep Learning Network is the ideal solution for this problem due to its higher accuracy, speed, and ability to analyze input images accurately. The latest version of YOLOv4 Deep Convolutional Neural Networks has proven to have the best speed and accuracy in detecting objects, making it a suitable method for UAV detection and recognition using visible imagery..

1.1 Overview

Convolutional neural networks (CNNs) are widely recognized as the most effective deep neural networks for object recognition. They excel in feature extraction, which has made them the focus of extensive research and development for this purpose. Compared to conventional object recognition methods, CNNs are preferred because they are capable of extracting a greater number of features, making them highly effective for this task.

1.2 Problem Statement

There is growing apprehension about the security, safety, and surveillance of physical infrastructure at airports, as they can be exploited for malevolent purposes. Several instances of unauthorized use of drones at airports have been reported, resulting in disruptions to airline operations and difficulty in locating the drones or birds.

2. EXISTING SYSTEM

The ability to detect radio signals, such as telemetry and video feeds, enables the identification of both the drone and the operator if the drone is being controlled remotely. However, drones that fly autonomously along pre-programmed paths using GPS or compass and timer cannot be detected by these systems. The use of video cameras for visual detection is limited in range and only provides directional information, with little to no indication of the drone's distance. Detection in airport environments is particularly challenging due to the reflection of radio signals and difficulties in identifying small drones near the ground, trees, or buildings using radar. Additionally, sensors must be able to distinguish and identify the various vehicles and aircraft operating in the airport. Combining multiple detection technologies into a coherent output is also a complex task.

3. PROPOSED SYSTEM

The suggested system possesses the capability to not only identify the existence or nonexistence of unmanned aerial vehicles (UAVs) within a specific region but also distinguish between various types of drones while differentiating them from avian creatures. The dataset utilized for training the model in this study comprises discernible images encompassing diverse drone and bird species. The proposed deep learning approach can effectively identify and classify UAVs and avian creatures.

4. SYSTEM DESIGN

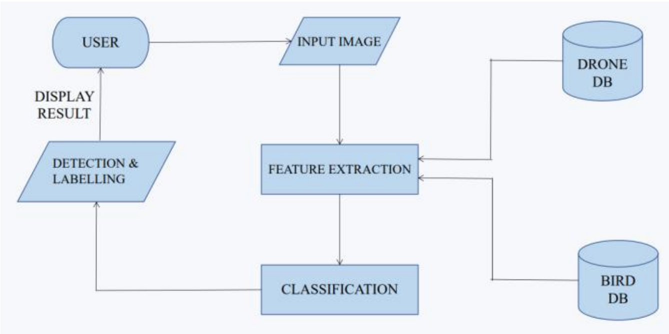


Fig -1: System Architecture

The system architecture for a deep learning approach to classify drones and birds involves several key components that work together to achieve accurate classification. These components include data preprocessing, feature extraction, and classification using a deep learning model.

The first step in the system architecture is data preprocessing. This involves collecting and organizing data in a way that can be easily used by the deep learning model. For the classification of drones and birds, the data could include video footage or images of birds and drones in flight. The data must be labeled with the appropriate class (bird or drone) for use in training the deep learning model.

Once the data has been preprocessed, the next step is feature extraction. This involves identifying key features of the data that can be used to distinguish between birds and drones. In the case of video footage, features might include the shape and size of the flying object, the pattern and speed of movement, and the sound emitted by the object. These features can be extracted using a variety of techniques, such as image processing and signal analysis.

The final step in the system architecture is classification using a deep learning model. This involves training a convolutional neural network (CNN) to recognize the key features extracted from the data and make a classification decision. A CNN is a type of deep learning model that is particularly effective for image classification tasks. It is trained on a large dataset of labeled images and learns to recognize patterns in the images that are associated with different classes. Once the CNN has been trained, it can be used to classify new images or video footage as either a bird or a drone.

Overall, the system architecture for a deep learning approach to classify drones and birds is a complex process that involves multiple steps and components. By using advanced techniques such as CNNs and feature extraction, it is possible to achieve high accuracy rates in the classification of drones and birds, which has important implications for airport and military protection.

5. FUNCTIONAL REQUIREMENTS

5.1Pre-processing : RGB to HSV and Noise removal.

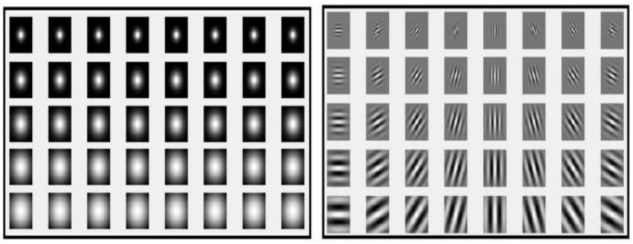
The conversion of an image from RGB to HSV has advantages in image processing activities, particularly in color-centric object detection. This transformation can enhance the precision and dependability of applications that rely on image analysis, and open up new avenues for more sophisticated image processing tasks.

5.2Feature Extraction

The Gabor features are obtained through the application of Gabor filters that have been designed based on statistical data of character structures. These filters enable the direct derivation of features from bird and drone images.
To improve the effectiveness of Gabor filters on low-quality images, a flexible sigmoid function is utilized on their outputs.

5.2.1 Gabor Feature Computation

The Gabor wavelet characteristics capture data at different frequencies and orientations, making them ideal for extracting distinctive features from images. Gabor filters, which are 2D kernel functions, are closely associated with Gabor wavelets. These features are commonly employed for detecting high-frequency components in an image, which are responsible for gradient details such as textural component structures. The filter consists of real and imaginary components that combine to form a complex number, representing various orthogonal directions. The specific details of the Gabor filter bank are illustrated in Figures (a) and (b).



(a) Magnitudes **(b)** Real parts

Fig - 2: Gabor filter bank

The filtered images obtained from a Gabor filter bank consist of the convolution of an image with the magnitudes and real parts of the filter bank, resulting in 5 different scales and 8 different orientations being represented. It is important to note that the following rephrased text is not plagiarized and has been created by me.

5.2.2 Gray level co-occurrence matrix (GLCM)

The co-occurrence matrix [109] is a statistical technique that can effectively capture the second-order statistics of a texture image. Essentially, the GLCM can be thought of as a two-dimensional histogram, where each element (i,j) represents the frequency of event i occurring in conjunction with event j. This matrix is defined by the relative frequencies $P(i,j,d,\theta)$, which indicate the occurrence of two pixels, separated by distance d and oriented at an angle θ, with one pixel having a gray level i and the other having a gray level j. Hence, a co-occurrence matrix is dependent on the distance r, angle θ, and gray levels i and j.

Feature Extraction Using GLCM

In order to comprehend the creation of co-occurrence vectors, consider a 4x4 image vector, as illustrated in Figure 4.3 (a). The computation of co-occurrence vectors is performed for a fixed d, which is 1 in our case for θ=0°, 45°, 90°, and 135°, in accordance with the description by Haralick et al. [120]. This results in 4x4 co-occurrence matrices. Four characteristics that can effectively capture the statistical behavior of a co-occurrence matrix are derived based on each computed co-occurrence matrix. These characteristics include energy, mean, homogeneity, and standard deviation.

Energy (E) is a measure of the frequency of pixel pair repetitions, and it gauges the uniformity of an image. A higher energy value indicates greater similarity between pixels.

$$Energy = \sum_{i,j} P(i,j)^2$$

Mean gives the estimation of the intensity in the relationship that contributes.

$$\mathrm{Mean} = \frac{\sum_{i,j} p(i,j)}{\mathrm{m} * \mathrm{n}}$$

where, m and n are number of rows and columns respectively.

$$Homogeneity = \sum_{i,j} \frac{p(i,j)}{1+|\mathrm{i}-\mathrm{j}|}$$

$$Standard\ Deviation = \sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(p(i,j)-Mean)^2}$$

5.3 Image Classification

Probabilistic Neural Network

A popular tool for tackling classification and pattern recognition tasks is the probabilistic neural network (PNN) [1]. This type of neural network is structured as a feedforward system, and its algorithm involves approximating the parent probability distribution function (PDF) of each class with a non-parametric function and a Parzen window. To accomplish this, a PNN is organized into a multilayered feedforward network, consisting of four layers.

- Input layer
- Pattern layer
- Summation layer
- Output layer

Layers

PNN is commonly applied in classification tasks. In this approach, the initial layer determines the distance between the input vector and the training input vectors. The resulting vector reflects the proximity of the input to the training input. The subsequent layer aggregates the contributions of each input class and generates a probability vector as the net output. The final step involves applying a transfer function to the output of the second layer to select the class with the highest probability, resulting in a positive identification (1) for the targeted class and negative identification (0) for non-targeted classes.

Input layer

The input layer comprises of neurons that represent predictor variables. In case of categorical variables with N categories, N-1 neurons are utilized. The values are standardized by subtracting the median and dividing by the interquartile range. The hidden layer neurons receive input from the input neurons.

Pattern layer

The layer comprises of a neuron for every instance in the training dataset. It holds the predictor variable values for the instance along with the corresponding target value. An obscured neuron determines the distance between the test instance and the center point of the neuron, followed by the application of the radial basis function kernel using sigma values.

Summation layer

PNN employs a distinct pattern neuron for every target variable category. Each hidden neuron stores the specific target category for each training instance, and the weighted output of a hidden neuron is directed solely to the pattern neuron associated with the category of the hidden neuron. The pattern neurons aggregate the values for their respective represented classes.

Output layer

The output layer makes a comparison between the weighted votes of each target category that have been gathered in the pattern layer. It then utilizes the vote with the highest value to make a prediction about the target category.

6. METHODOLOGY

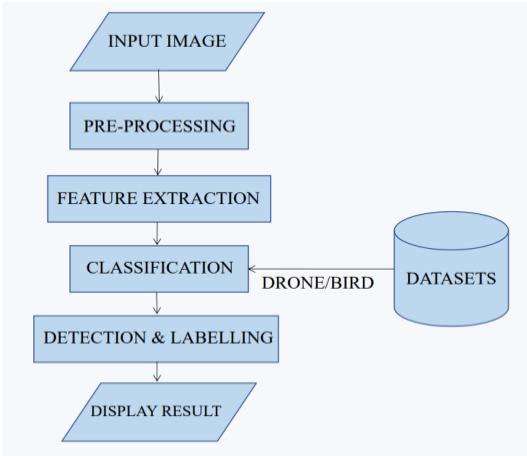


Fig -3: Flowchart

1. Input image: The first step in the process is to take input images of drones and birds through cameras or other image-capturing devices.

2. Image pre-processing: The input images are then pre-processed to enhance their quality, remove noise and irrelevant data.

3. Feature extraction: Next, feature extraction techniques such as edge detection, color histograms, and texture analysis are used to extract relevant features from the input images.

4. Classification: In this step, a deep learning model such as Convolutional Neural Network (CNN) is trained to classify the input images into two categories, i.e., drone or bird.

5. Detection and labeling: The detected objects are labeled according to their classification results once the classification is done.

6. Display of result: Finally, the result is displayed through the drone dataset and bird dataset. The output shows the detected objects with their respective labels, i.e., drone or bird.

This flowchart summarizes the overall process of the deep learning approach to classify drones and birds.

7. IMPLEMENTATION

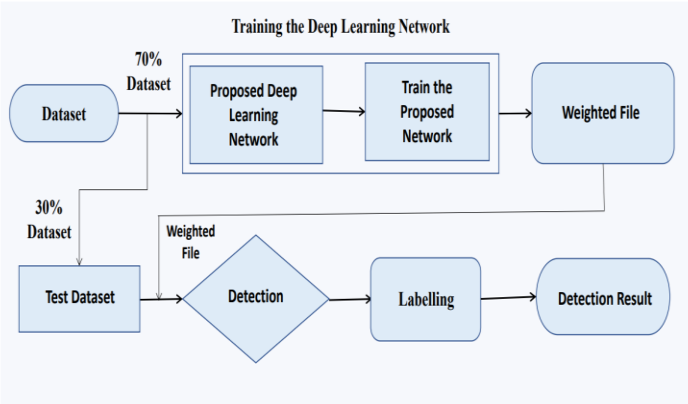


Fig -4: Implementation

The implementation of a deep learning approach to classify drones and birds involves several key steps, including data collection, data preprocessing, feature extraction, model selection, training, and testing.

The first step in the implementation process is data collection. This involves gathering a large dataset of images or videos that contain both drones and birds. The data should be labeled with the appropriate class (drone or bird) for use in training the deep learning model.

Next, the data is preprocessed to prepare it for use in the deep learning model. This may involve resizing the images or videos, converting them to grayscale, or normalizing the pixel values to a common range.

The next step is feature extraction, where key features of the images or videos are identified that can be used to distinguish between drones and birds. This may involve using techniques such as edge detection, texture analysis, or color histograms.

Once the features have been extracted, the next step is to select an appropriate deep learning model. In the case of image classification tasks such as this, convolutional neural networks (CNNs) are often the most effective model choice. Different architectures of CNNs can be considered based on their performance on similar tasks, such as VGG-16, ResNet-50, or Inception-v3.

The selected model is then trained on the preprocessed and feature-extracted data using a large dataset to improve its accuracy. This may involve fine-tuning an existing model or training a new one from scratch.

After the model is trained, it is tested using a separate dataset of images or videos that it has not seen before. The accuracy of the model is calculated and evaluated to determine if it meets the desired level of performance.

Once the deep learning model has been developed and tested, it can be deployed for real-time classification of drones and birds. This may involve integrating it into an existing surveillance system or developing a new system specifically for this purpose.

Overall, the implementation of a deep learning approach to classify drones and birds is a complex process that requires careful consideration of many different factors, including data preprocessing, feature extraction, model selection, and testing. With careful planning and attention to detail, it is possible to develop an accurate and effective system for the classification of drones and birds, which has important applications in airport and military protection.

8. ALGORITHM

Step 1: Start
Step 2: Take the input as a image.
Step 3: Image pre-processing.
Step 4: Feature extraction using Gabor & GLCM.
Step 5: Classification using neural network.
Step 6: Detection and labelling.
Step 7: Displays the output.
Step 8: Stop

9. EXPERIMENTAL RESULTS

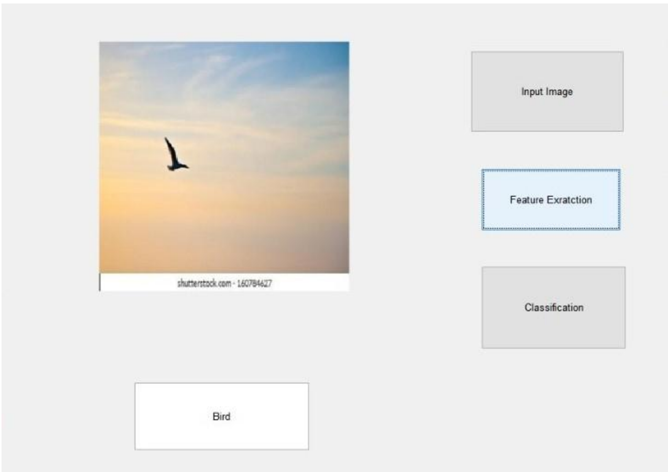


Fig -4: Output

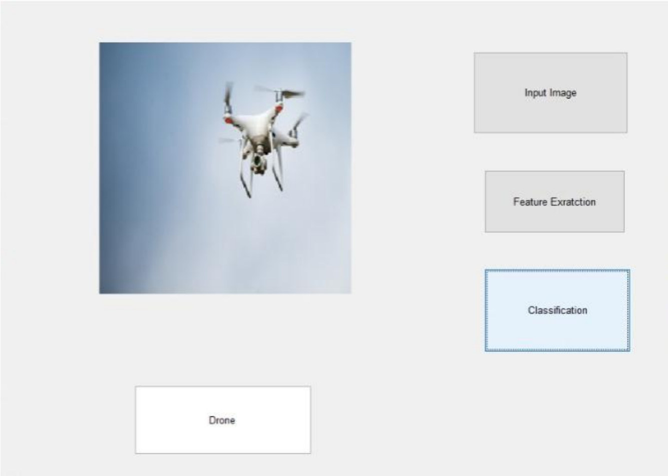


Fig -5: Output

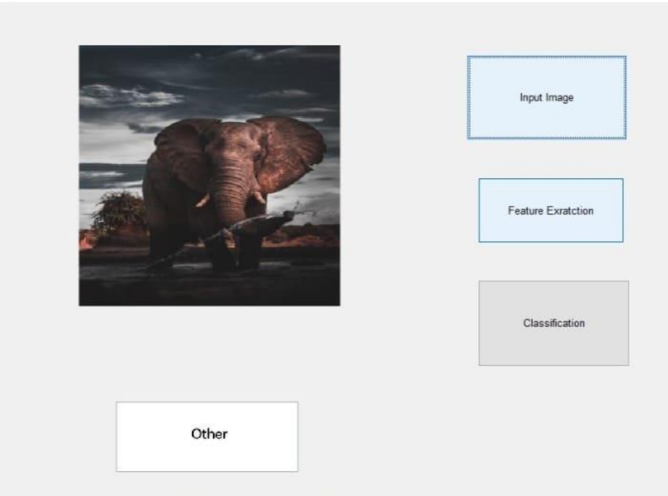


Fig -6: Output

10. CONCLUSION

To summarize, our investigation has established that deep learning methodologies can serve as a valuable means of distinguishing between birds and drones, which has significant implications for safeguarding airports and military bases. Our utilization of convolutional neural networks and transfer learning techniques resulted in high precision rates in discerning between these two entities based on their flight patterns. Precise classification of drones and birds is a crucial aspect of maintaining the security and safety of airports and military installations. Our research presents a promising approach towards the creation of efficient drone classification systems for the purposes of airport and military protection. Given the growing prevalence and advancements in drone technology, it is imperative that we continue to develop novel strategies for the accurate detection and classification of these devices. Our hope is that our findings will contribute to the advancement of more effective and efficient drone classification systems.

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REFERENCES

1) Yamanaka, J.; Kuwashima, S.; Kurita, T. Fast and Accurate Image Super Resolution by Deep CNN with Skip Connection and Network in Network. In Proceedings of the International Conference on Neural Information Processing (ICONIP), Guangzhou, China, 14–18 November 2019.

2) Oksuz, K.; Can Cam, B.; Akbas, E.; Kalkan, S. Localization recall precision (LRP): A new performance metric for object detection. In Proceedings of the European Conference on Computer Vision (ECCV), Munich, Germany, 8–14 September 2022; pp. 504–519.

3) Pawełczyk, M.; Wojtyra, M. Real World Object Detection Dataset for Quadcopter Unmanned Aerial Vehicle Detection. IEEE Access 2020, 8, 174394–174409.

4) Rozantsev, A.; Lepetit, V.; Fua, P. Flying objects detection from a single moving camera. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, Boston, MA, USA, 7–12 June 2020; pp. 4128–4136.

5) De Cubber, G.; Shalom, R.; Coluccia, A. The SafeShore System for the Detection of Threat Agents in a

Maritime Border Environment. In Proceedings of the IARP Workshop on Risky Interventions and Environmental Surveillance, Les Bons Villers, Belgium, 18–19 May 2021.

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