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Bird and Drone Image Classification Using ResNet CNN: A Deep Learning Approach for Aerial Surveillance

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Abstract−Accurate classification of bird and drone images is crucial in supporting aerial surveillance and security systems, particularly to distinguish between natural objects such as birds and man-made objects such as drones. Manual classification methods have limitations in terms of speed and accuracy, thus necessitating a more efficient and reliable technology-based approach. This study aims to implement a ResNet-50 based Convolutional Neural Network (CNN) architecture to automatically classify bird and drone images. The dataset used was obtained from the Kaggle platform and consists of two classes: Bird and Drone, with a total of 22,407 images. The data was split into training (17,323 images), testing (844 images), and validation (1,740 images). All images underwent preprocessing and augmentation steps to enhance data quality and model training performance. The model was developed using the ResNet-50 architecture, which is well-regarded for handling complex image classification tasks. Evaluation results show that the model achieved an accuracy of 92%. For the Bird class, a precision of 0.83 and a recall of 0.99 were obtained, while for the Drone class, precision reached 0.99 and recall was 0.86. The average F1-score of 0.92 indicates that the model delivers balanced and reliable performance in the binary image classification task.

Keywords: Image Classification; CNN; ResNet-50; Bird; Drone

1. INTRODUCTION

Unmanned aerial vehicles (UAVs) or drones have become one of the most significant technological innovations in recent years, with applications spanning various sectors. These include precision agriculture [1]-[4], military operations [5]-[8], logistics and delivery services [9]-[11], and environmental monitoring and disaster management [12]. The growing use of drones highlights their potential to improve the efficiency and effectiveness of diverse human activities [13]-[15].

However, the increased presence of drones in airspace introduces new challenges, particularly in terms of visual object recognition [16]-[18]. A critical issue is the difficulty in distinguishing drones from natural entities such as birds [19]. Due to similar visual characteristics when observed from a distance or under suboptimal conditions [20]-[23], distinguishing between these objects becomes complex. Misidentifying drones and birds can result in errors in surveillance systems, jeopardize airspace security, and even impact wildlife conservation efforts [24]-[27]. Consequently, an intelligent and efficient image classification system is required to accurately differentiate between these objects [28]-[30].

One effective approach for image classification is the use of Convolutional Neural Networks (CNNs) [31]-[35], particularly the ResNet (Residual Network) architecture [36]-[39]. ResNet was designed to address the issue of accuracy degradation encountered when CNNs become deeper [40]-[43]. This architecture introduces skip connections (or identity shortcut connections), enabling information to bypass one or more layers without distortion. This feature accelerates model convergence and enhances its ability to learn complex features [44]-[46]. These characteristics make ResNet highly suitable for large-scale image recognition, detection, and segmentation tasks [47]-[49]. Additionally, ResNet has shown superior performance in terms of accuracy and resistance to overfitting compared to standard CNNs [50]-[52]. The flexibility of ResNet, with its different configurations (e.g., ResNet-18, ResNet-50, ResNet-152), allows it to adapt to datasets of varying complexity [53]-[56].

Research on bird image classification has previously utilized architectures such as MobileNetV2, which has been employed to classify bird species with high accuracy. For instance, a study trained a model using 58,388 images from 400 bird species, achieving a 92% accuracy, though with a loss value of 0.8835 [57]. Another study applied CNN for bird image classification, reaching an accuracy of 96.30% on training data and 81.33% on validation data after 20 epochs [58]. However, no previous studies have focused on the classification of both birds and drones within a single model, creating a clear research gap.

This study aims to fill this gap by developing a classification model based on the ResNet CNN architecture to distinguish between bird and drone images. Unlike prior research, which concentrated on a single object type or employed basic CNN models, this study adopts the deeper and more complex ResNet architecture. The novelty of this work lies in its application of ResNet to classify two visually similar aerial objects in a single classification system. The primary contribution of this study is the development of a ResNet-based CNN model capable of accurately distinguishing between birds and drones, along with an in-depth evaluation of its performance metrics. The findings of this research are expected to support the development of automated surveillance and aerial object detection systems for security and environmental conservation purposes.

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2. RESEARCH METHODOLOGY

2.1 Research Stages

To ensure that the results are scientifically accountable, this research was conducted empirically, logically, and systematically—from problem formulation to report preparation. Figure 1 presents the structure of the proposed research stages.

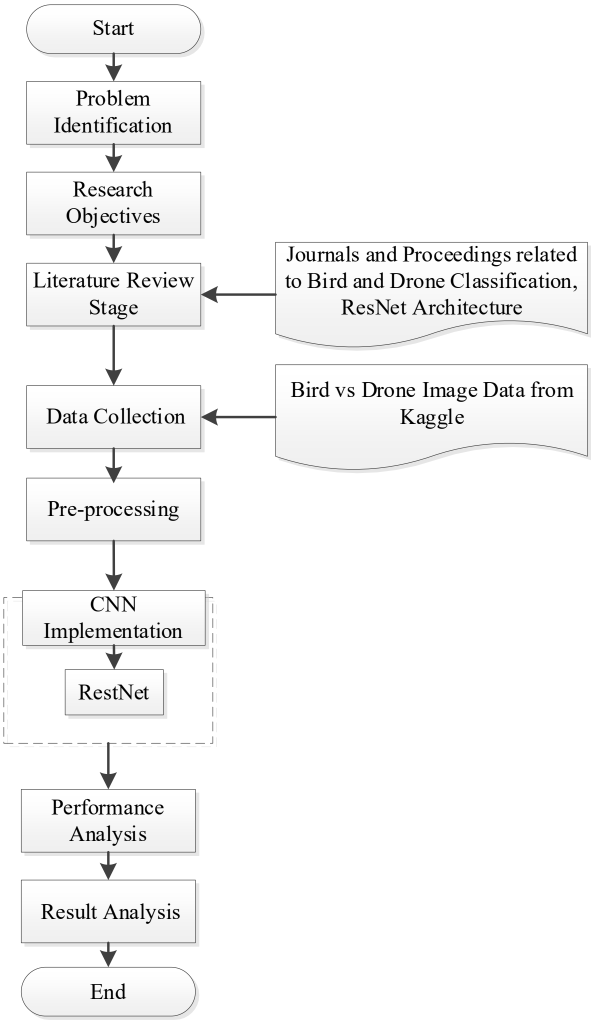

Figure 1. Research Stages

The figure illustrates the research workflow for bird and drone image classification using a ResNet-based Convolutional Neural Network (CNN) architecture. The process begins with the initiation phase, which includes problem identification, setting research objectives, and collecting relevant literature on bird and drone classification as well as the ResNet architecture. This is followed by the data collection stage, where image data is gathered from Kaggle, consisting of two classes: birds and drones. Once the data is obtained, a pre-processing stage is carried out to prepare the data before model training. The CNN implementation is then performed using the ResNet architecture as the primary model. After the model is built, performance analysis is conducted by measuring evaluation metrics such as accuracy, precision, recall, and F1-score. The results of the performance analysis are further examined to gain a deeper understanding of the model's effectiveness. The final stage involves formulating solutions or conclusions that can be used for further development. This diagram represents a systematic and structured workflow in conducting deep learning-based research for binary image classification.

2.2 Problem Identification

The main challenge addressed in this research is the difficulty in visually distinguishing between birds and drones, especially in automated surveillance systems. Both share similar characteristics, such as size, shape, and movement patterns, making them hard to differentiate from a distance or under suboptimal conditions [59]-[60]. Studies show that drones and birds can appear visually similar, particularly when flying at similar altitudes or when observed in varying lighting and camera resolutions [61]-[62]. This highlights the need for a more accurate AI-based image classification system. While CNNs have proven effective in many image classification tasks, deeper architectures like ResNet are

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necessary to overcome accuracy degradation and improve the differentiation of objects with similar visual features. This research aims to evaluate the performance of ResNet in classifying birds and drones, addressing these challenges.

2.3 Research Objectives

The objective of this research is to evaluate the capability of the ResNet-based Convolutional Neural Network (CNN) architecture in accurately and efficiently performing image classification between birds and drones. The evaluation is conducted by assessing the model's performance through key metrics such as accuracy, precision, recall, and F1-score to measure how well the model can distinguish between natural and artificial aerial objects. Additionally, this study aims to identify the ResNet variant or configuration that is most suitable and optimal for this two-class classification task, considering both the accuracy of the results and training time efficiency. Consequently, the findings of this research are expected to contribute to the development of reliable computer vision–based surveillance systems and serve as a reference for selecting deep learning models for similar image classification tasks in the future.

2.4 Literature Review Stage

In the literature review stage, previous studies related to bird and drone image classification were examined to establish the foundation for understanding CNN models, particularly the ResNet architecture. This review assessed the performance of basic CNN models and highlighted their limitations in classifying objects with similar visual features, such as birds and drones. For instance, studies on bird classification using CNNs have reported accuracy rates ranging from 81% to 96%, but with challenges related to overfitting and poor generalization on unseen data [57]-[58]. In contrast, ResNet has shown superior performance due to its deep architecture and the introduction of skip connections, which help overcome accuracy degradation and improve model convergence, especially for complex classification tasks [40]-[43].

By comparing the results and metrics of previous studies with this research, it becomes clear that while simpler CNN models struggle with differentiating visually similar objects, ResNet's ability to handle deeper architectures without overfitting makes it a more suitable choice for the task at hand. This comparison underscores the decision to adopt ResNet for the two-class image classification task in this study..

2.4.1 RestNet

ResNet (Residual Network) is a CNN architecture introduced to address the accuracy degradation problem in very deep networks. By utilizing residual learning and skip connections [63]-[65], ResNet enables smoother information flow between layers, resulting in more stable and accurate training [66]-[68].

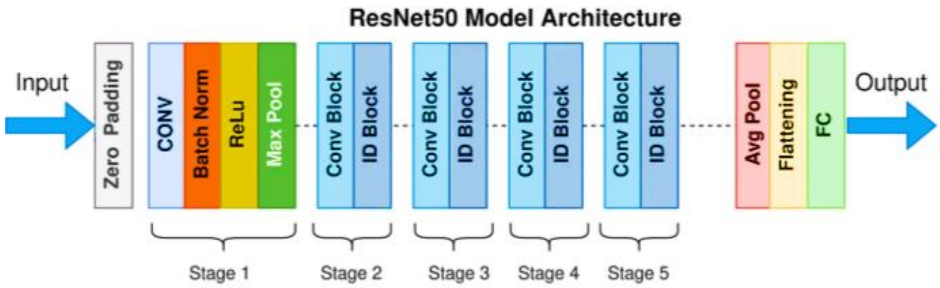

Figure 2. RestNet Architecture

The image illustrates the ResNet50 architecture, a widely used variant of the Residual Network (ResNet) for image classification tasks. The architecture begins with a Zero Padding stage followed by a basic convolutional layer (Stage 1) that includes Convolution, Batch Normalization, ReLU activation, and Max Pooling. Subsequently, the model consists of five main stages (Stage 2 to Stage 5), each composed of a combination of convolutional blocks (Conv Blocks) and identity blocks. These blocks incorporate shortcut connections designed to address the vanishing gradient problem common in very deep networks. After the feature extraction stages, the output undergoes Average Pooling, Flattening, and passes through a Fully Connected (FC) layer to produce the final classification output. This structure enables training of deep networks without loss of accuracy, making ResNet50 highly effective for large-scale image recognition.

The choice of ResNet50 for this study, as opposed to other variants such as ResNet18 or ResNet101, was based on its balanced trade-off between performance and computational efficiency [69]-[73]. ResNet18, being a shallower network, may not capture the complex features required for distinguishing between visually similar objects like birds and drones [74]-[77]. On the other hand, ResNet101, although deeper, could be computationally more expensive and may lead to longer training times with diminishing returns for the given dataset size [78]-[80]. ResNet50 offers a good compromise, providing deep feature extraction capabilities while maintaining manageable computational costs, making it well-suited for this task [81]-[82].

2.5 Data Collection

The initial step in the data collection process involved obtaining images from the Kaggle website [83]. This study focuses on two object classes: bird and drone. The total number of images used amounts to 20907, with the distribution detailed in Table 1.

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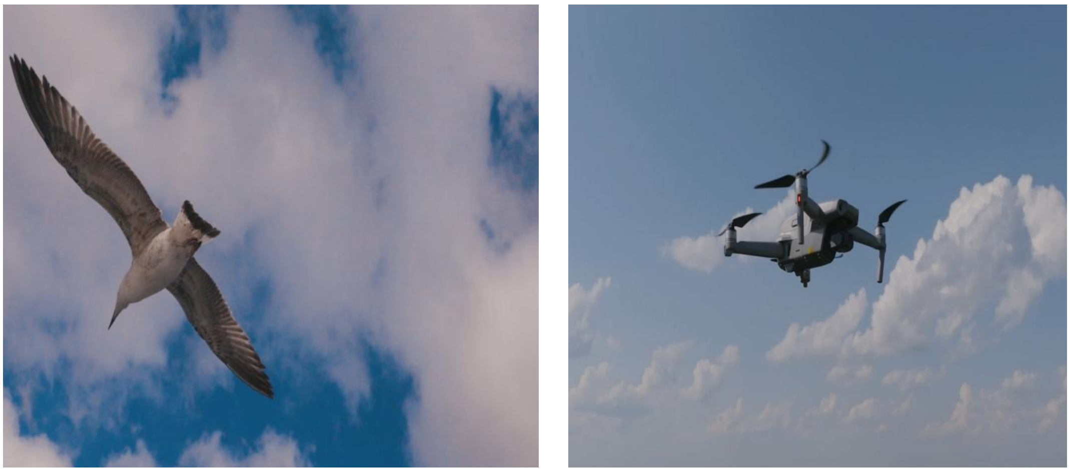
Table 1. Number of Images

No	Object Types	Amount
1	Bird	8406
2	Drone	12501
	Total	20907

The data in Table 1 is sourced from Kaggle, where the images have already been categorized by their respective classes. Prior to training, several preprocessing and augmentation steps were applied to the images to improve model performance. The preprocessing steps included resizing all images to a consistent size, normalizing pixel values, and converting images to grayscale where necessary. Augmentation techniques, such as random rotations, flipping, and zooming, were applied to increase the diversity of the dataset and prevent overfitting. These preprocessing and augmentation methods ensured that the model could generalize better to unseen data and enhance its ability to classify bird and drone images accurately.



(a) (b)

Figure 3. Object Image Types: (a) Bird (b) Drone

Both images depict objects flying in the air but have very distinct characteristics. The first image (a) shows a bird, featuring an organic body shape, clearly visible feathers on its wide, curved wings, and a natural flying posture beneath a cloudy sky. The bird appears to be flapping its wings to maintain altitude and flight direction. In contrast, the second image (b) displays a drone, a man-made flying machine with four propellers that act as both propulsion and stabilizers. The drone has a symmetrical shape, with rigid, metallic surfaces and an aerodynamic design. Unlike the bird, the drone includes indicator lights and rapidly spinning propellers. Although both are airborne, the differences in shape, material, and flight patterns are striking-making the classification between birds and drones a significant challenge in computer vision-based image recognition.

3. RESULT AND DISCUSSION

3.1 Image Data Pre-processing Results

At this stage, data preparation is carried out before processing with the model. This step includes data cleaning as well as splitting the data into training, validation, and testing sets. The data division resulting from this stage is as follows:

Table 2. Image Dataset Partitioning

Data Splitting	Class	Amount
Training	Bird	7389
	Drone	10934
Testing	Bird	316
	Drone	528
Validation	Bird	701
	Drone	1039

Data splitting in this study follows common practices, with approximately 70% of the data allocated for training, 15% for validation, and 15% for testing. This split ratio is chosen to ensure that the model has enough data for training while also having sufficient data for validation and testing to evaluate its performance effectively. The training data is used to train the model to recognize patterns from each object class. The validation data is used to evaluate the model's

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performance during training, helping to fine-tune the model and prevent overfitting. During the training phase, the test data is used to assess the final performance of the model on unseen data.

In addition to data splitting, data augmentation techniques were applied to enhance the dataset and improve model generalization. Augmentation methods such as random rotations, flipping, scaling, and zooming were applied to the training images. These techniques artificially increase the diversity of the training data, helping the model to learn more robust features and preventing overfitting by exposing the model to a wider range of image variations. The use of augmentation ensures that the model performs well on real-world data, which can vary in terms of orientation, scale, and other factors.

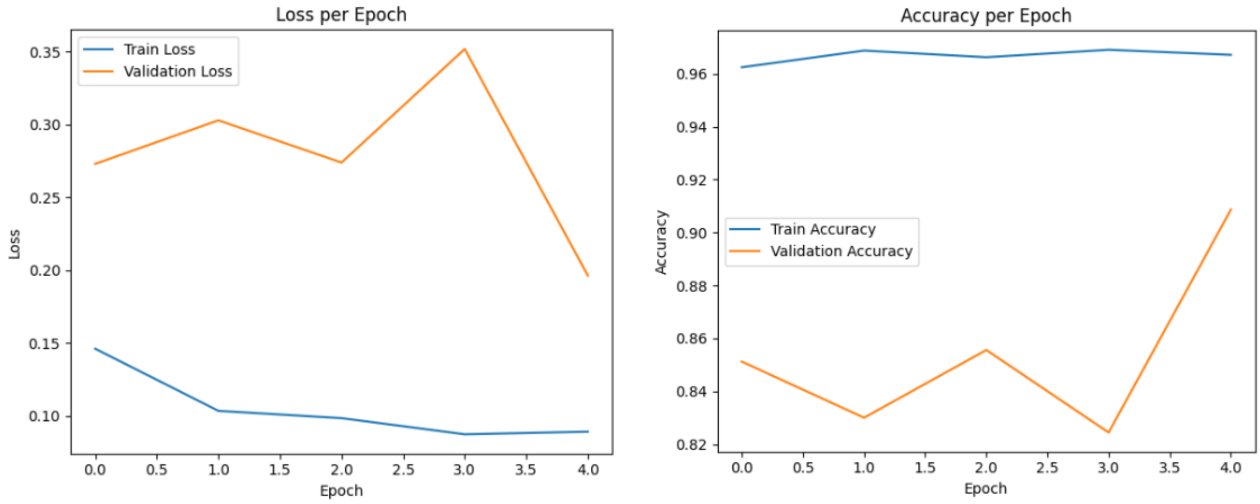
3.2 CNN Implementation

In the implementation phase, the CNN architecture used is ResNet, which is known for its ability to overcome the vanishing gradient problem and enable training of deeper networks. The ResNet model was successfully implemented to distinguish between two image classes, namely birds and drones. Training results showed that the model achieved high accuracy on the validation data, indicating that important features of each class were well recognized. During the training process, the loss consistently decreased and accuracy increased, demonstrating good model convergence. Additionally, visualization of the confusion matrix showed that the model was able to correctly classify the majority of images, although some misclassifications likely occurred due to the visual similarity between flying birds and drones in certain poses. Overall, the CNN implementation using ResNet proved effective for the task of bird and drone image classification.

3.3 Performance Analysis

3.3.1 Image Classification Training Results

The training process was monitored through loss and accuracy values. The following are the results of the image classification training.



(a) (b)

Figure 4. (a) Training Loss and (b) Training Accuracy of ResNet

The training process was carried out with specific parameters to optimize the model's performance. A batch size of 32 was chosen, as it offers a balance between computational efficiency and model convergence. This batch size allows the model to process a sufficient number of images at once, enabling faster learning while maintaining accuracy. The learning rate was set at 0.001, which is a commonly used value for fine-tuning deep learning models. This learning rate ensures that the model updates its weights effectively without making overly large adjustments that could destabilize training. Additionally, the model was trained for 5 epochs, providing enough iterations to allow the model to learn from the data while avoiding excessive training that could lead to overfitting. These chosen parameters ensured that the model trained efficiently, resulting in smooth curves in both the loss and accuracy graphs, indicating that the model was able to learn and generalize effectively.

3.3.2 Image Classification Evaluation Results

The image classification evaluation results were analyzed using a confusion matrix, which serves to measure how well the model successfully classifies images. This analysis provides insights into the model's performance in identifying each class, including the number of correct predictions and the errors occurring in each category.

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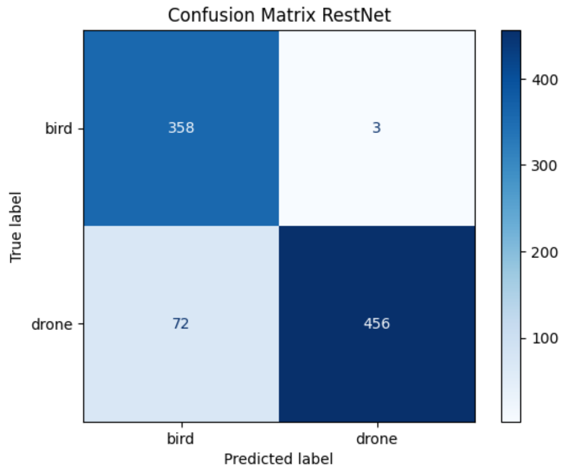

Figure 5. Confusion Matrix of ResNet

Based on the confusion matrix, the ResNet model demonstrates very good performance in classifying bird and drone images. Out of a total of 889 test samples, 358 bird images were correctly classified as birds, while only 3 bird images were misclassified as drones. Meanwhile, out of 528 drone images, 456 were correctly recognized, but 72 drone images were misclassified as birds. These results indicate that the model has a high accuracy in recognizing birds, with a very low false positive rate for this class.

Figure 6. Effect of Backlight, Low Resolution on Prediction

Terdapat jumlah kesalahan yang relatif lebih tinggi dalam mengenali drone, di mana beberapa gambar drone masih diklasifikasikan sebagai burung. Masalah ini dapat dikaitkan dengan faktor-faktor tertentu seperti cahaya latar dan gambar beresolusi rendah. Misalnya, gambar drone dengan pencahayaan yang buruk atau resolusi rendah mungkin tampak mirip secara visual dengan burung, sehingga model lebih sulit untuk mengidentifikasinya dengan benar. Dalam kasus cahaya latar, bentuk dan siluet drone dapat menyerupai burung, yang menyebabkan kesalahan klasifikasi. Selain itu, gambar beresolusi rendah dapat mengaburkan fitur-fitur utama drone, yang semakin mempersulit identifikasinya.

Tantangan-tantangan ini menyoroti potensi masalah dalam sistem pengawasan udara, di mana kesalahan deteksi objek drone dapat memengaruhi langkah-langkah keamanan. Secara keseluruhan, meskipun ResNet berkinerja baik dalam mendeteksi burung, masih ada ruang untuk perbaikan dalam identifikasi drone, terutama dalam kondisi yang memengaruhi kejernihan gambar, seperti cahaya latar dan resolusi rendah.

3.3.3 Image Classification Prediction Results

Next, the ResNet model was tested on data by providing five images from each object class, namely Bird and Drone, resulting in an average of correct predictions. Figure 14 illustrates the prediction results alongside the actual object images.

Figure 7. Prediction Results of Testing with ResNet

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Figure 7 shows the visualization of ResNet model predictions on several test images from two classes, namely bird and drone. Among the four sample images displayed, the first two were correctly classified as birds, consistent with their true labels. Meanwhile, in the following two images, there was one misclassification where a drone image was predicted as a bird (indicated by the red text "Predicted: Bird"), while the other drone image was correctly classified.

3.4 Result Analysis

The results show that the ResNet model handles complex datasets with high inter-class similarity quite well. The complete evaluation results are presented in Table 3.

Table 3. Evaluation Results of the Model

Classification Report:				
	precision	recall	f1-score	support
Bird	0.83	0.99	0.91	361
Drone	0.99	0.86	0.92	528
accuracy			0.92	889
macro avg	0.91	0.93	0.91	889
weighted avg	0.93	0.92	0.92	889

The evaluation results of the ResNet model are presented in the classification report above. The model achieved an overall accuracy of 92% in classifying two classes, namely Bird and Drone. For the Bird class, the model showed a precision of 0.83, recall of 0.99, and an F1-score of 0.91, indicating that nearly all Bird images were correctly recognized, although some Bird images were mistakenly classified as Drone. Conversely, for the Drone class, the model recorded a very high precision of 0.99 but a recall of only 0.86, showing that while almost all Drone predictions were correct, there were still a considerable number of Drone images that were not accurately recognized.

Macro average calculates the precision, recall, and F1-score by treating all classes equally, without considering their support (i.e., the number of samples in each class). In this case, the macro average values for precision (0.91), recall (0.93), and F1-score (0.91) indicate that the model performs quite well on average across both classes.

Weighted average, on the other hand, takes into account the support (number of samples) of each class, giving more weight to the performance on the larger class (in this case, Drone). The weighted average values for precision (0.93), recall (0.92), and F1-score (0.92) reflect a slightly better overall performance, as the Drone class has more samples, and the model performs very well on this class.

While the model shows strong performance, especially with Bird classification, there is a noticeable imbalance in performance between the two classes. The recall for Drone is lower (0.86) compared to Bird (0.99), which indicates that the model has a harder time recognizing drones, particularly under certain conditions such as backlighting or low resolution.

4. CONCLUSION

This research demonstrates that the ResNet architecture effectively classifies aerial images into birds and drones, achieving an accuracy of 92% and an F1-score of 0.92. The model excels at identifying birds but shows more errors in classifying drones, likely due to the visual similarity between the two, especially under challenging conditions like backlighting and low resolution. To improve Drone classification, future research could focus on data augmentation, fine-tuning the model with adjusted class weights, and exploring advanced techniques like ensemble models or attention mechanisms. Despite these challenges, ResNet remains a strong choice for aerial image classification, and this study paves the way for the development of efficient, real-time computer vision systems for aerial monitoring, especially for devices with limited computational resources, such as drones.

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