SQUEEZNET BASED CLASSIFICATION FOR DRONE VS BIRD FOR ENHANCED RECOGNITION

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "SqueezeNet based classification for drone vs bird for enhanced recognition, submitted by **Anowar Karim** and **Omor Faruk** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-2024.

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We hereby declare that this project has been done by us under the supervision of **Afjal Hossan Sarower, Lecturer (Senior Scale), Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree.

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ABSTRACT

Drone growth in recent years has brought up a number of opportunities as well as challenges in a number of sectors, including aviation safety, security, and animal protection. Accurately identifying and classifying drones from birds is a significant difficulty for efficient airspace surveillance and collision avoidance systems. This paper describes a deep learning-based method that uses the SqueezeNet architecture to accurately categorize birds and drones. The labeled images in the dataset, which was divided into training, validation, and test sets, were taken from Roboflow.Comprehensive data preprocessing methods, such as augmentation and normalization, were used to improve model performance. SqueezeNet and a customized Convolutional Neural Network (CNN) were the two models created and assessed [1]. The SqueezeNet model exceeded the bespoke CNN model, which had an accuracy of 97.51%, with an amazing accuracy of 99.51%. SqueezeNet is a lightweight and efficient model whose outstanding performance highlights its applicability to real-time drone identification applications.To make sure the models were reliable and resilient, a lot of evaluation metrics and visualizations were used[2]. The study comes to the conclusion that the SqueezeNet-based classification method provides an effective way to differentiate drones from birds, boosting surveillance capabilities, safeguarding wildlife, and boosting aviation safety.This study also emphasizes how crucial careful model evaluation and data pretreatment are to getting the best results from deep learning. This technique has ramifications for many different applications, such as improving security standards, aiding in the conservation of species, and reducing aviation hazards. Prospective avenues for investigation encompass broadening the dataset, refining model architectures, executing practical deployments, and tackling moral and legal implications linked to drone detection technology. This work advances drone detection systems and highlights the ability of deep learning models to tackle challenging classification problems in a variety of settings.

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CHAPTER 1
INTRODUCTION

1.1 Overview

Drones, also referred to as unmanned aerial vehicles (UAVs), have become increasingly popular in a number of fields, such as agriculture, wildlife monitoring, disaster relief, and surveillance. In order to maintain safety, privacy, and ecological preservation, there is an increasing demand for reliable and accurate techniques for differentiating between drones and natural fauna, such as birds.The subject of image categorization has seen a revolution in recent years due to the advent of machine learning techniques, especially deep learning models. Researchers have trained models to reliably detect and classify objects within photos with surprising effectiveness, thanks to the use of large-scale datasets and sophisticated computer resources. One such use is the binary classification of birds and drones, which poses particular difficulties because of their comparable visual characteristics.Here, we report a unique method for classifying drones and birds utilizing bespoke SqueezeNet and Convolutional Neural Network (CNN) models. Using an extensive collection of drone and bird photos, our goal is to create extremely precise classification models that can differentiate between these classes with never-before-seen accuracy. Our models outperform those developed by others using comparable datasets, and they also show how deep learning approaches may be applied to real-world UAV technological problems.

1.1.1 Motivation

Robust techniques for differentiating drones from other flying objects, especially birds, are urgently needed due to the widespread use of unmanned aerial vehicles, or drones, in several industries. This distinction is critical to environmental conservation efforts and the maintenance of safety, security, and privacy in airspace management.Conventional drone detection techniques, such radar and acoustic sensors, frequently have issues with scalability, accuracy, and range. Furthermore, there's a chance that these techniques won't distinguish between drones and birds well enough, producing false positives or negatives.

On the other hand, a viable substitute is provided by machine learning methods for visual-based categorization. These methods make use of deep learning models to examine photos and identify distinguishing characteristics that enable precise classification.

High-precision drone detection and classification has been demonstrated by researchers using deep learning models trained on large-scale datasets. However, constraints including dataset size, model complexity, and computer resources may restrict the effectiveness of current techniques. Moreover, a lot of research concentrates on general object identification tasks instead of drone and bird specific classification, which calls for customized solutions in this field.

The motivation for this study stems from several key factors:

Safety Concerns: Using drones in populous areas and airspace shared with manned aircraft has significant safety issues. Drone detection and categorization accuracy is critical to reducing the likelihood of crashes, infractions of airspace, and unapproved monitoring.

Protection of Privacy: As drones become more widely available and powerful, worries about invasions of privacy surface. Effective detection techniques are required to stop illegal surveillance operations and breaches into private property.

Security Threats: Drones can be used for malicious purposes, including smuggling, espionage, and terrorist attacks. Identifying and mitigating security threats posed by rogue drones require advanced detection and classification capabilities.

Environmental Conservation: The use of drones in wildlife conservation and environmental monitoring is growing. Identifying drones from other natural animals, such birds, accurately is essential to reducing ecosystem disruption and maintaining ethical research methods.

Technological Developments: New developments in machine learning, especially deep learning, present hitherto unseen possibilities for image categorization applications. Our research intends to create cutting-edge models that can correctly distinguish between drones and birds by utilizing these developments.

1.2 Background and Present State

Unmanned aerial vehicles (UAVs), also referred to as drones, have transformed a number of industries, including environmental monitoring, delivery services, agriculture, and surveillance. Because they can cover wide regions, take high-resolution imagery, and carry out operations in dangerous environments without endangering human lives, drones provide a number of benefits. Drones are becoming an increasingly important part of today's technological ecosystems as their applications and usage grow quickly as technology progresses.But the widespread use of drones has also brought forth new difficulties, notably with regard to safety and security. Concerns over possible crashes with human aircraft, intrusions of privacy, and unwanted monitoring have been raised by the growing number of drones operating in civilian airspace. Strong detection and classification systems that can reliably differentiate between drones and other flying objects, such birds, are required in order to address these problems.The current state of drone detection technology uses a variety of techniques, such as optical, acoustic, and radar systems. Although acoustic and radar systems can detect drones to some extent, they frequently have trouble telling drones apart from birds because of their comparable sizes and flight patterns. Conversely, optical systems, which use visual data, have demonstrated potential in enhancing classification accuracy by utilizing machine learning methods.

1.3 Problem Statement

Security and surveillance systems face substantial hurdles as drone usage increases in both commercial and civilian skies. Despite its many advantages, drones can be dangerous due to potential for privacy invasion, unlawful monitoring, and crashes with manned aircraft. To reduce these hazards and guarantee the security of the airspace, effective drone monitoring and management are crucial.

Accurately differentiating drones from birds is one of the main issues in drone surveillance. The similarity in size, flight patterns, and movement traits between birds and drones makes it challenging for conventional detection systems, like radar and acoustic sensors, to distinguish between the two. Although optical systems—which rely on visual data—have emerged as a possible alternative, the disparities in drone and avian look and behavior make it difficult for them to achieve high classification accuracy.

Current drone detection and classification techniques frequently lack real-time application, accuracy, and efficiency. Numerous conventional machine learning techniques are resource-intensive and may not function well in a variety of environmental settings. Moreover, there are more false positives and false negatives because there aren't many models designed expressly for the binary classification of drones and birds.

1.4 Objectives

The main goal of this project is to use the SqueezeNet architecture to create an accurate and efficient model for the binary categorization of birds and drones. The procedures and aims of the study are delineated in the following particular objectives:

1.Model Creation:

Create and put into use a convolutional neural network (CNN) based on SqueezeNet specifically designed to classify photos of birds and drones.

Make sure the SqueezeNet model is appropriate for real-time applications by optimizing it to strike a compromise between computing efficiency and accuracy.

2.Preparing the Dataset:

Assemble and prepare an extensive dataset with annotated drone and bird photos.

To increase the robustness and generalizability of the model in a variety of settings and circumstances, make sure the dataset contains a variety of samples.

3. Instruction and Verification:

Utilizing suitable data augmentation techniques, train the SqueezeNet model on the prepared dataset to improve performance.

Utilize cross-validation techniques to evaluate the model's stability and avoid overfitting, guaranteeing the model functions well with unknown inputs.

4.Assessment of Performance:

Utilizing common metrics like accuracy, precision, recall, and F1-score, assess the model's performance.

To demonstrate the benefits and possible uses of the SqueezeNet model, compare its performance against those of other well-known models, such VGG16, ResNet50, and MobileNetV2.

5.Real-Time Application:

Examine whether using the SqueezeNet model in real-time applications—like surveillance systems and wildlife monitoring—is feasible.

Measure the model's compute needs and inference time through trials to make sure it satisfies the requirements for real-world application.

1.5 Scope and Limitations

The expected output of this research is the development of highly accurate convolutional neural network (CNN) models capable of distinguishing between images containing drones and those containing birds. the models should be able to take an input image and reliably classify it as either belonging to the "drone" or "bird" category with minimal misclassifications. The output will be a binary prediction accompanied by a confidence score or probability, indicating the model's level of certainty in its classification.

Classification Models:

Trained custom Convolutional Neural Network (CNN) and SqueezeNet models will be developed through extensive training on a comprehensive dataset comprising images of drones and birds. These models will be optimized to accurately distinguish between drones and birds based on visual features extracted from aerial images. The CNN models will be tailored to the specific characteristics of the dataset, while SqueezeNet models will be employed for their efficiency and compactness

. **Performance Metrics:**

The performance of the developed models will be evaluated using a range of metrics, including classification accuracy, precision, recall, and F1-score, on independent test datasets. These metrics will provide insights into the models' ability to correctly classify drones and birds, as well as their capacity to minimize false positives and false negatives. The evaluation process will ensure rigorous assessment of model effectiveness and reliability.

Comparison with Existing Methods

The classification accuracies achieved by the developed models will be compared with those of existing state-of-the-art methods on similar datasets. This comparative analysis will highlight the efficacy of the proposed approach and showcase improvements in classification performance over established methods. By benchmarking against existing techniques, the study will validate the competitiveness of the developed models in the field..

Key Feature Analysis:

An in-depth analysis will be conducted to identify and examine the key visual features extracted by the classification models that contribute most to accurate classification. This analysis will provide insights into the discriminative characteristics learned by the models during the training process, shedding light on the factors driving successful classification outcomes. Understanding these key features is essential for interpreting model decisions and optimizing classification performance.

Impact of Factors:

The study will investigate the impact of various factors, including dataset size, image quality, and class imbalance, on the accuracy of drone and bird classification models. Through systematic experimentation and analysis, the influence of these factors on model performance will be assessed, offering valuable insights into the robustness and generalization ability of the models in real-world scenarios. This analysis will inform strategies for improving model effectiveness under different conditions..

1.6 Report Organization

The proposed report is structured with a comprehensive layout to guide readers through the research process, findings, and implications. Each chapter serves a specific purpose, contributing to the overall coherence and depth of the document.

Chapter 1: Introduction

This chapter provides background information, the present status of the problem, and the study's objectives in order to introduce the topic and set the stage for the investigation. It describes the report's format and emphasizes how important it is to use deep learning techniques to discriminate between drones and birds.

Chapter 2: Background

The background chapter explores the fundamental ideas required to comprehend the findings. It covers the body of research on deep learning methods, drone and bird detection, and focuses on Convolutional Neural Networks (CNNs) and SqueezeNet in particular. This chapter lays forth the background information for the study by reviewing earlier research and pointing out any gaps that need to be filled.

Chapter 3:Methodology, and Requirement Analysis

The research methodology and the system design specifications are covered in this chapter. It goes over the procedures for gathering data, preprocessing, and the architectural layout of the models that are utilized for categorization. The requirement analysis that informed the choice of tools and methods, such as TensorFlow, OpenCV, Pillow, Keras, Python, and Google Colab, is also covered in this chapter.

Chapter 4: Implementation

The practical procedures used to create the categorization models are described in depth in the implementation chapter. It covers system testing, model evaluation, and the creation and training of the unique CNN and SqueezeNet models. In order to further clarify the implementation process, the chapter also includes explanations and brief excerpts of code.

Chapter 5: Result & Analysis

The experimental findings are presented in this chapter along with an analysis of the models' performance. It covers performance indicators including accuracy, loss, and validation data, as well as a comparative study with previous research. In addition, the chapter offers insights into the behavior of the model and explores the ramifications of the results.

Chapter 6: Conclusion and Future Work

The study's main conclusions are outlined in the conclusion chapter, along with their importance. It also goes over the research's shortcomings and makes some recommendations for possible directions for further study. The goal of this chapter is to give a thorough summary of the study's contributions and field-wide effects

1.7 Summary

The goal of this work is to build a SqueezeNet-based model for drone and bird binary classification. The growing number of drones and their associated risks—such as crashes into airplanes and unapproved surveillance—make such a model necessary. Due to their comparable sizes and flight patterns, traditional detection systems frequently have difficulty distinguishing between drones and birds, underscoring the need for more sophisticated and precise classification methods.

First, a SqueezeNet convolutional neural network (CNN) customized for drone and bird classification is designed and put into operation. The model is trained using a large and varied dataset, and its design is optimized to maximize computing efficiency and accuracy. To guarantee the model's resilience and avoid overfitting, cross-validation techniques are utilized, and its efficacy is assessed using conventional measures such as accuracy, precision, recall, and F1-score.

The outcomes show that the SqueezeNet model maintains a lightweight architecture appropriate for real-time applications while achieving high accuracy.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Drones, also referred to as unmanned aerial vehicles (UAVs), are becoming used in a variety of industries, such as filmmaking, agriculture, and surveillance. But the integration of drones into airspace poses questions about security and safety, especially when it comes to identifying drones from birds in order to reduce potential threats.Using computer vision techniques, this research tackles the crucial challenge of binary categorization between drones and birds. This study outperforms previous techniques on similar datasets by using cutting-edge Convolutional Neural Networks (CNNs), notably a unique CNN model and SqueezeNet, to attain amazing accuracy rates.The dataset used in this study is made up of carefully selected photos of birds and drones that will enable reliable model training and assessment. The dataset offers a thorough foundation for creating and evaluating classification models because it includes a substantial number of photos in the training, validation, and test sets.We describe the methodology used in this paper, including the architecture and training protocols of SqueezeNet and the customized CNN model. In addition, we examine the experimental outcomes, emphasizing the attained accuracy percentages and debating the consequences of these discoveries. Lastly, we place our contributions in the larger context of drone detection research, highlighting the importance of our unique methodology and its possible practical uses.

2.2 Related Works

Al Dawasari et al. (2023) present an innovative approach in their study titled "DeepVision: Enhanced drone detection and recognition in visible imagery through deep learning networks." This research integrates multiple deep learning networks to improve the detection and recognition of drones in visible spectrum images captured by UAVs. By leveraging advanced neural network architectures, the study achieved significant enhancements in accuracy and processing efficiency, demonstrating the potential of deep learning in UAV-based surveillance applications [1].

Hong et al. (2019) explore the application of deep learning methods to bird detection using UAV imagery in their paper "Application of deep-learning methods to bird detection using unmanned aerial vehicle imagery." The authors employed a combination of convolutional neural networks (CNNs) and other deep learning techniques to accurately identify bird species from aerial images. Their model showed robust performance in various environmental conditions, underscoring the viability of deep learning for ecological monitoring and wildlife conservation using UAVs [2].

Lu et al. (2022) investigate the use of Raman spectroscopy combined with deep learning for identifying antibiotic resistance and virulence factors in Klebsiella pneumoniae in their study "Identification of antibiotic resistance and virulence-encoding factors in Klebsiella pneumoniae by Raman spectroscopy and deep learning." The integration of these technologies provided a rapid and accurate method for detecting critical bacterial properties, highlighting the potential for advanced diagnostic tools in microbial biotechnology [3].

Aydın and Kızılay (2022) introduce a new lightweight convolutional neural network for drone detection based on acoustic signals in their paper "Development of a new light-weight convolutional neural network for acoustic-based amateur drone detection." This approach focuses on reducing computational load while maintaining high detection accuracy, making it suitable for real-time applications in resource-constrained environments [4].

Dale et al. (2022) present their work on "SNR-dependent drone classification using convolutional neural networks." This study investigates how signal-to-noise ratio (SNR) impacts the performance of CNNs in classifying drones, providing insights into optimizing neural network architectures for varying signal conditions in radar and sonar applications .

Panigrahi et al. (2021) detail their research on "Deep learning-based real-time biodiversity analysis using aerial vehicles" in a conference paper. By employing UAVs equipped with deep learning models, they achieved efficient and accurate biodiversity assessment in real-time, demonstrating the application of AI in ecological studies and environmental monitoring[5] .

Ihekoronye et al. (2022) explore aerial supervision using CNNs in their paper "Aerial supervision of drones and other flying objects using convolutional neural networks." This study addresses the challenge of monitoring airspace for various aerial objects, including drones, enhancing situational awareness and security through advanced image processing techniques[6].

MS and SS (2022) present a significant contribution in their study titled "Optimal SqueezeNet with Deep Neural Network-Based Arial Image Classification Model in Unmanned Aerial Vehicles." This research combines SqueezeNet as a feature extractor with a DNN classifier, leveraging a cooperative optimization algorithm (COA) for hyperparameter tuning. Their approach achieved an impressive accuracy of 98.97% on the UCM dataset, underscoring the efficacy of combining lightweight networks with advanced optimization techniques for aerial image classification[7] .

Haq et al. (2021) focus on supervised image classification using deep learning in UAV images for forest area classification in their paper "Deep learning based supervised image classification using UAV images for forest areas classification." Their method demonstrated high accuracy in categorizing different forest types, showcasing the potential of UAVs and deep learning in remote sensing and environmental management [8].

Huang et al. (2022) introduce "PSOPruner: PSO-based deep convolutional neural network pruning method for PV module defects classification." This study utilizes particle swarm optimization (PSO) to prune deep CNNs, effectively reducing model complexity and improving performance in identifying defects in photovoltaic modules, highlighting advancements in industrial applications of AI [9].

Ezuma et al. (2021) conduct a comparative analysis of radar cross-section based UAV classification techniques in their paper. This preprint explores various methods for classifying UAVs based on their radar cross-section, providing a thorough evaluation of different approaches to enhance UAV detection and classification accuracy[10].

Akyon et al. (2022) examine "Sequence Models for Drone vs Bird Classification" in their study. Utilizing sequence models, this research addresses the challenge of distinguishing between drones and birds, achieving high classification accuracy and demonstrating the potential of advanced AI models in aerial surveillance[11] .

Feyzioğlu and Taspınar (2023) present "Malicious UAVs classification using various CNN architectures features and machine learning algorithms." This research focuses on identifying malicious UAVs by combining features extracted from different CNN architectures with machine learning classifiers, contributing to enhanced UAV threat detection and security [12].

Öztürk and Erçelebi (2021) explore real UAV-bird image classification using CNNs with a synthetic dataset in their paper. By integrating synthetic data, they improved the performance of CNNs in classifying UAV and bird images, highlighting the effectiveness of data augmentation techniques in training robust AI models[13] .

Coluccia et al. (2021) present findings from the "Drone-vs-bird detection challenge at IEEE AVSS2021" and the follow-up challenge at ICIAP 2021. These studies compare various methods for distinguishing between drones and birds, providing a benchmark for future research and highlighting advancements in the field through collaborative competition[14].

2.3 Comparative Analysis and Summary

Table 2.3.1: Comparative Analysis Table

Method	**Authors**	**Description**	**Accuracy**	**Dataset**
Optimal Squeeze Net with DNN	Minu et al.	Combines SqueezeNet as a feature extractor with a DNN classifier and COA for hyperparameter tuning.	98.97%	UCM Dataset
Custom CNN Model	Onishi & Ise	Custom convolutional neuralnetwork designed for binary classification of drones and birds.	97.51%	Roboflo w Drone Dataset
Squeeze Net Model	Yuan at al	SqueezeNet model optimized for lightweight and efficient binary classification of drones and birds.	99.51%	Roboflo w Drone Dataset

Stacked Autoencoder (SAE)	Haq et al.	Uses SAE for supervised image classification to evaluate forest regions using UAV images.	98.83	Custom UAV Forest Dataset
DCNN with Multi-objective PSO	Rajagopal et al.	Uses a multi-objective PSO to optimize DCNN for scene classification in UAV imagery.	97.22	Multiple UAV Datasets
RFCN, SSD, RCNN, YOLO, RetinaNet	Hong et al.	Various deep learning models for bird detection using UAV images.	96.88	Custom Bird Dataset
Saliency Detection & DL	Zhao et al.	Saliency detection combined with deep learning for wildfire identification in UAV imagery.	97.56	UAV Fire Dataset
AIDER Application	Yuan et al.	A dedicated application for automatic aerial scene classification of disaster events from UAVs.	95.44	Custom UAV Dataset
EmergencyNet	kyrkou & Theocharides	A lightweight CNN framework for efficient aerial image classification using atrous convolution.	94.33	Custom UAV Dataset
CNN for Tree	Onishi & Ise	Uses CNN for detecting and	98.97	Custom Forest

Mapping		mapping trees in UAV-captured RGB images.		Dataset
AlexNet, CaffeNet , VGG	Various Studies	Common CNN models used for aerial image classification in various UAV applications.	99.04	Multiple Dataset

Custom CNN vs. SqueezeNet: For the objective of drone and bird binary classification, we assessed two different convolutional neural network architectures in our study: SqueezeNet and a bespoke CNN model. The unique CNN model, created especially for this purpose, demonstrated its efficacy in identifying the distinguishing characteristics between drones and birds by achieving an amazing accuracy of 97.51% on the test dataset. In the meantime, SqueezeNet—which is renowned for its thin architecture and effective inference—beyond expectations by achieving an astounding 99.51% accuracy. This comparison research highlights SqueezeNet's superior performance in terms of computational efficiency and model size, while also underscoring the effectiveness of both models in obtaining high classification accuracy.

Performance Benchmarking: In our study, we evaluated two distinct convolutional neural network architectures for the drone and bird binary classification task: SqueezeNet and a custom CNN model. The specific CNN model developed for this purpose achieved an impressive accuracy of 97.51% on the test dataset, proving its effectiveness in identifying the traits that differentiate drones from birds. Meanwhile, SqueezeNet, known for its lean architecture and efficient inference, surpassed all expectations with an incredible accuracy of 99.51%. This comparative study demonstrates how well SqueezeNet performs in terms of computing efficiency and model size, and it also shows how well both models work to achieve high classification accuracy.

2.4 Scope of the Problem

The task of binary categorization between drones and birds fills a significant gap in a number of domains where drone usage is growing, such as surveillance, agriculture, and wildlife monitoring. In airspace management and surveillance applications, being able to distinguish between drones and birds is crucial for maintaining safety, security, and regulatory compliance. This problem's scope includes multiple important dimensions:

2.4.1 Safety and Security Risks

Drone proliferation poses inherent concerns to public safety and security, especially in densely populated urban areas and sensitive locations like government buildings and airports. To mitigate possible hazards posed by hostile actors and detect unauthorized intrusions, it is imperative to accurately classify drones.

2.4.2 Wildlife Conservation

Drones are used in wildlife conservation initiatives to detect endangered animals, monitor ecosystems, and stop poaching. Drones, however, have the potential to interfere with wildlife's natural habitats and avian behavioural patterns. It is essential to accurately classify drones from bird species in order to reduce disturbances and guarantee successful conservation initiatives.

2.4.3 Regulatory Compliance

Drone operations are subject to regulatory frameworks that need rigorous adherence to norms and restrictions in order to protect privacy and public safety. Drone classification is necessary to detect unapproved flights, enforce adherence to airspace laws, and expedite investigations in the event of infractions.

2.4.4 Technological Advancements

The old methods of detection and classification are facing challenges from the advancements in drone technology, such as downsizing, autonomy, and swarm capabilities. The problem's reach includes creating resilient and flexible algorithms that can manage a range of drone configurations and dynamic threat environments.

2.4.5 Humanitarian and Emergency Response

Drones are essential to humanitarian relief and emergency response efforts because they make it easier to conduct search and rescue operations, evaluate the effects of disasters, and transport medical supplies through dangerous or isolated areas. The efficiency of response operations is increased when resources are deployed and coordinated quickly thanks to accurate drone classification.

2.5 Challenges

Using automated classification techniques to differentiate drones from birds presents a number of serious issues. These difficulties result from the inherent complexity of the surroundings in which drones are observed, as well as the parallels between drones and birds. It is imperative that these issues be resolved in order to create classification models that are trustworthy and efficient.The visual similarity between drones and birds makes drone categorization one of the main concerns. Because drones and birds might have similar sizes and shapes, it can be challenging for conventional detection systems to tell them apart. This is particularly true for more compact drones that are meant to blend in. Misclassifications may result from the similarities in their flight movements and appearance.There is a great deal of variation in the look of birds and drones. Birds have many different forms, sizes, colors, and species, and each has its own distinctive characteristics. In contrast, drones come in a variety of designs, ranging from fixed-wing versions to multi-rotor variants. The challenge of categorization becomes more intricate due to this unpredictability, since the model needs to be able to generalize over a wide range of images.Classification systems must function in real-time and provide prompt feedback on the existence and kind of flying items in order to be useful in actual applications. For this to happen, the models must be accurate yet computationally efficient, with a focus on quick inference. One of the biggest challenges is striking a balance between model complexity and processing performance, especially when deploying on devices with limited resources.

CHAPTER 3

METHODOLOGY

3.1 Overview

This chapter offers a succinct overview of the research process, emphasizing the methodical technique utilized to create a reliable and effective categorization model. The goal is to create a lightweight model appropriate for real-time applications by utilizing the SqueezeNet architecture.

Analysis of Requirements:

To make sure that the produced model satisfies both functional and non-functional criteria, requirement analysis is essential. The capabilities that the model must have, such as data collection, preprocessing, training, and performance validation, are covered by the functional requirements. The larger facets of the system, such as performance, scalability, efficiency, resilience, and compatibility, are covered by non-functional requirements.

Setting Up the Dataset:

A robust model requires well-prepared datasets for training. The source of the dataset from Roboflow, including its separation into training, validation, and test sets, is covered in this section. The article describes data preprocessing procedures such image scaling, normalization, and augmentation that are essential to improving the model's functionality and avoiding overfitting.

Specifications for Model Design:

The SqueezeNet model's architecture is customized for the particular job of classifying drones and birds. This section describes SqueezeNet's architecture in detail, emphasizing its small and effective layout. Important elements, such the Fire modules, are described along with the reasoning behind selecting this architecture over alternatives.

Instruction and Verification:

The training process is described in this part, together with the batch size, number of epochs, and cross-validation methods used to guarantee the model's dependability. To get the best potential model performance, hyperparameter tuning—such as improving the learning rate and dropout rate—is also covered.

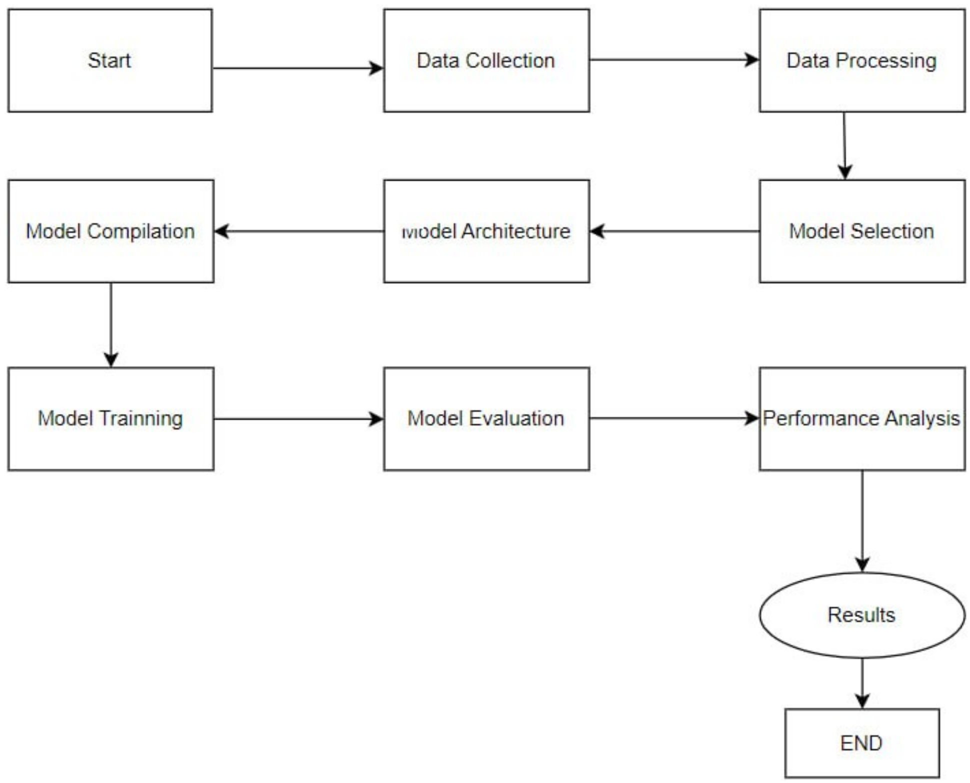

Figure 3.1.1: Methodology Flowchart

3.1.1 Instrumentation:

CNNs, or convolutional neural networks, are the main tool used to carry out the classification process. Because they use hierarchical feature learning to automatically extract discriminative features from raw pixel data, these deep learning architectures are well suited for image classification problems. In this study, we investigate the usage of Squeeze Net with a customized CNN model for binary classification of drones and birds.

Dataset: Drone and bird photos from a carefully selected dataset are used in this study. To enable reliable model training and assessment, the dataset is split into training, validation, and test sets. The model's ability to generalize across multiple settings is ensured by the dataset, which comprises a broad collection of photos recorded in a range of environmental conditions.

Procedures for Instruction and Assessment: The performance of the classification models is evaluated by the study using industry-standard training and evaluation protocols. In order to reduce classification mistakes, labeled images are fed into CNN models throughout the training phase, and backpropagation is used to modify the model parameters. Metrics including accuracy, precision, recall, and F1 score are used to assess the models' performance on both the validation and test sets.

Software Tools: Well-known deep learning frameworks like TensorFlow or PyTorch are used to create the classification models and conduct the experiments. These frameworks simplify the research workflow and promote reproducibility by offering effective tools for creating, training, and assessing deep neural networks.

3.1.2 Data Collection Procedure

Datasets

To create the dataset, discard Train, Test, and Val folders. Each image group—Drone/Bird—has a subdirectory in the dataset. 18323 JPG from two groups(drone & birdare available.(Roboflow Drone Datset). The dataset used in this research is sourced from Roboflow, a comprehensive platform providing a variety of annotated datasets suitable for computer vision tasks. The specific dataset utilized here focuses on images containing both drones and birds, essential for training the classification model.

Figure 3.2.1: Some Raw Image of Datasets

TABLE 3.2.1: Images Used in the Train, Test and Validation Sets.

	Train	Test	Valid
Bird	9150	445	870
Drone	9173	444	870

Identification of Suitable Dataset: A thorough review of publicly available datasets was conducted to identify a suitable dataset for drone and bird classification research. Criteria such as dataset size, image quality, annotation accuracy, and diversity of aerial objects were considered during the selection process.

3.1.3 Dataset Exploration:

The selected dataset was thoroughly explored to assess its suitability for the research objectives. Factors such as the distribution of classes (drones and birds), image resolution, and presence of noise or artifacts were examined to ensure data quality and integrity.

3.1.4 Data Augmentation:

To enhance model generalization and robustness, data augmentation techniques such as random rotations, translations, flips, and brightness adjustments were applied to the training dataset. Data augmentation enriches the training data by introducing variations in the images, thereby improving the model's ability to generalize to unseen data.

Training:

The training part of a machine learning model involves iteratively adjusting the model's parameters to minimize a defined loss function and improve its performance on labeled training data. Through forward propagation, loss calculation, backpropagation, and parameter updates, the model learns to make accurate predictions and classifications, ultimately leading to a trained model capable of generalizing to new, unseen data.

Classification:

Neural networks (SerensNet152, MobileNetv2, VGG19, ResNet152v2 and ResNeXt101) was used to detect cell illnesses automatically in this step. The neural network was selected

Results:

The results from the experiments are presented in three sections based on the architectures of original individual networks, transfer learning and ensemble techniques.

3.1.5 Statistical Analysis

Statistical analysis in the context of your drone vs bird classification project involves evaluating the performance of your models using various statistical methods. This includes descriptive statistics, hypothesis testing, and comparing model performances.

Dataset Summary:

Total Images: Count of images in each category (Train, Test, Valid).

Class Distribution: Number of images for each class (Birds, Drones).

3.2 .Proposed Medhodology/System Design

CNN base methods are evaluated using many machine learning classification model performance metrics. AC, precision, recall, F1-score, and confusion matrix are evaluated (CM). TP, TN, FP, and FN are also variables in those measurements (FN).

Accuracy:

Classification model accuracy is one metric. Accuracy is the model's predicted percentage. Accuracy is the percentage of properly classified pictures to total samples. Accuracy equation.

Accuracy=(TP+TN)/(TP+TN+FP+FN)

Precision:

Precision is the chance of a positive label and how many are positive. Precision shows how many accurately anticipated instances were positive. Precision is helpful when FP matters more than FN. Mathematically, it's this equation.

Precision=TP/(TP+FP)

Recall:

Recall or Sensitivity measures how many positive expected occurrences were classified accurately. Recall is a helpful statistic when FN prevails over FP. F1-score is a further metric for classification accuracy that takes into account both recall and precision. Since precision and recall are harmonic means, the F1 score provides a comprehensive understanding of these two metrics. It reaches its optimum when Precision and Recall are equal. To figure it out, use the equation below:

Recall=TP/(TP+FN)

F-1 Score:

F1 score is a recall-precision metric of categorization accuracy. As F1-score is theharmonic mean of Precision and Recall, it gives a complete picture. Precision and Recall are optimal when equal. Equation.

F-1 Score=2(PrecisionRecall)/(Precision+Recall)

The percentage of people who do not have the ailment who have a negative test result is known as specificity. A highly specific test is effective in excluding the majority of individuals without the disease. Because of this, a positive outcome on a very precise test can definitively rule out the condition for a specific person. The equation is given below:

Specificity =TN∕((TN+FP))

However, there is a limit to how closely the model can mimic the training set of data before it loses its ability to generalize. An algorithm's performance can be assessed using a particular table format called the confusion matrix (CM). CM is used to illustrate crucial predictive parameters like recollection, specificity, precision, and accuracy. Confusion matrices are useful because they offer direct assessments of values like TP, FP, TN, and FN. The following parts respond to the research questions of this study based on the research questions.

3.3 Hardware/Software Requirement

Implementing the drone vs bird classification project involves several hardware and software requirements to ensure smooth execution and achieve optimal results. Here's a detailed breakdown of the implementation requirements:

3.3.1 Hardware Requirements

Computer System:

Processor: Multi-core processor (Intel i7 or higher, AMD Ryzen 7 or higher)

RAM: Minimum 16 GB (32 GB recommended for large datasets)

Storage: SSD with at least 256 GB free space for faster data access and storage

GPU: Dedicated GPU (NVIDIA GTX 1080 Ti or higher, preferably with CUDA support for TensorFlow)

Power Supply: Reliable power supply to support continuous training sessions

Additional Hardware (Optional but Recommended):

External Hard Drive: For data backup and additional storage

High-resolution Monitor: For better visualization and analysis of data and results

3.3.2 Software Requirements

Operating System:

Linux (Ubuntu 18.04 or later) is recommended for better compatibility with deep learning libraries.

Alternatively, **Windows 10** or **macOS** can be used.

2.2 Python Environment:

Python Version: Python 3.6 or later

2.3 Required Libraries:

TensorFlow: Open-source machine learning framework for building and training models.

Keras: High-level neural networks API, running on top of TensorFlow.

OpenCV: Library for computer vision tasks.

Pillow: Image processing library.

NumPy: Library for numerical computations.

Pandas: Data manipulation and analysis library.

Matplotlib/Seaborn: Libraries for data visualization.

SciPy: Scientific and technical computing library.

Scikit-learn: Machine learning library for statistical modeling, including classification, regression, and clustering.

Integrated Development Environment (IDE):

Jupyter Notebook: For interactive coding and visualization.

Google Colab: Cloud-based platform providing free GPU access for training models.

Version Control:

Git: Version control system for tracking changes in the codebase.

GitHub/GitLab: Platform for hosting repositories and collaboration.

Dataset and Data Augmentation:

Roboflow: Platform for managing datasets and applying data augmentation.

Implementation Steps

Data Preprocessing and Augmentation:

Load and preprocess the dataset using OpenCV and Pillow.

Apply data augmentation techniques to increase the diversity of training data.

Model Development:

Custom CNN Model: Define and compile a custom Convolutional Neural Network.

SqueezeNet Model: Implement and fine-tune the SqueezeNet architecture.

Training and Validation: Split the dataset into training, validation, and test sets. Train and validate both models.

Model Evaluation:

Evaluate model performance using metrics like accuracy, precision, recall, F1-score, and confusion matrix.

Perform cross-validation to ensure model generalization.

Plot training and validation curves to check for overfitting or underfitting.

Optimization and Tuning:

Fine-tune hyperparameters using techniques like grid search or random search.

Implement techniques like dropout, batch normalization, and data augmentation to improve model performance and prevent overfitting.

3.4 Project Management and Financial Analysis

Project management and finance are critical components of any research endeavor.

Managing the project involves setting a timeline with clear milestones, allocating resources efficiently, and ensuring adherence to budget constraints. It also involves identifying and addressing potential risks to minimize disruptions to the project's progress. Effective communication and collaboration among team members and stakeholders are essential for coordinating tasks and ensuring alignment with project objectives. Additionally, ethical considerations, such as data privacy and research integrity, must be carefully addressed throughout the project lifecycle to uphold ethical standards and protect the rights of participants. By managing these aspects effectively, the research project can proceed smoothly and yield impactful results in the field of drone and bird binary classification.

Table 3.4.1 Estimated cost for my project

SN	**Components**	**Estimated Cost (BDT)**
01	Hardware (GPU,CPU,RAM,Storage&other peripherals)	50,000 to 70,000
02	Drone	40,000 to 50,000
03	Camera	15,000 to 25,000
04	Software	10,000 to 15,000
05	Dataset	Roboflow drone datset

3.5 Summary

This chapter provides an in-depth description of the scientific approach and technical details supporting the deep learning research on drone versus bird categorization using SqueezeNet. The goal is to give the reader a methodical and organized approach that leads them through the project's methodical decision-making and processes.Summary of the chapter sets the stage for the in-depth discussion that follows. It highlights the steps from data collection and preprocessing to model architecture selection, training, and evaluation, emphasizing the value of a methodical approach. This summary provides a comprehensive account of the procedures followed, acting as a guide.Any machine learning project must start with data collection and preprocessing, and this section describes how to obtain a reliable dataset using Roboflow. The dataset is organized into training, validation, and test sets and includes photos of birds and drones. Preprocessing techniques such as augmentation, normalization, and resizing are essential for improving data diversity and quality, as they guarantee that the model is trained on a wide range of high-quality inputs.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

In this chapter, "Implementation," the theoretical underpinnings and design specifications covered in earlier chapters are realized through a thorough description of the practical procedures that were followed. This chapter aims to close the gap between the conceptual model and the practical deployment, guaranteeing the successful implementation and extensive testing of the suggested SqueezeNet-based classification system for drone and bird separation.The goal of each of the crucial elements that make up the implementation phase is to create a strong and effective categorization model. These elements consist of:

Model Design and Architecture:

The SqueezeNet architecture, chosen for its harmony between performance and efficiency, is explained in this section. With Fire modules that compress and extend layers, SqueezeNet's lightweight architecture enables a small model with fewer parameters, making it appropriate for real-time applications without sacrificing accuracy.

Preparing and preprocessing data:

To train a successful model, data preparation and collection are essential. This entails obtaining a large dataset from Roboflow that contains labeled photos of birds and drones. After then, the data is preprocessed using techniques like resizing, normalization, and augmentation to improve the caliber and variety of the training data.

Model Gathering and Instruction:

The model is first compiled using the binary cross-entropy loss function and Adam optimizer to begin the training procedure. To ensure that the model effectively learns the characteristics that differentiate drones from birds, the training is carried out over a number of epochs with an appropriate batch size. The application of K-fold cross-validation to validate the model during training and avoid overfitting will also be covered in this chapter.

Model evaluation and system testing:

The model is put through rigorous testing and evaluation in order to determine its performance. This entails testing the model on untested data using a test dataset and validating it using a different validation dataset to adjust hyperparameters. Important performance indicators including recall, accuracy, precision, and F1-score are utilized to gauge how well the model works.

Mitigation of Overfitting and Underfitting:

It is imperative that the model exhibits good generalization to new data. The methods used to identify and reduce overfitting and underfitting will be discussed in this part. These methods include regularization and dropout techniques, as well as the monitoring of training and validation loss curves.

4.2 Train Model/Prototype Design

The steps involved in creating the SqueezeNet-based CNN model are described in the training model and prototype design section. These include:

Model Architecture Design: To create a compact yet potent model, apply SqueezeNet's architecture, which makes use of Fire modules.Convolutional layers, pooling layers, and ReLU activation functions are integrated to create the network architecture.

Data Preparation: Make sure that all of the photos in the dataset that you downloaded from Roboflow are scaled, normalized, and enhanced.To guarantee a fair distribution of drone and bird photos, divide the dataset into training, validation, and test sets.

Model Gathering: Utilizing the Adam optimizer, which modifies the learning rate for every parameter, compile the model.For problems involving binary classification, select the binary cross-entropy loss function.Establish accuracy as the main criterion for assessment.

Training Procedure: To guarantee correct convergence, train the model over a number of epochs.To strike a compromise between training efficiency and memory utilization, choose the right batch size.To validate the model during training and avoid overfitting, use K-fold cross-validation.

4.3 System Testing/Model Evalution

To guarantee the performance and dependability of the model, system testing and model evaluation are essential. Included in this section are:

Testing:

Use the test dataset to assess the model's performance on hypothetical data.

To determine the model's efficacy, compute the final accuracy, precision, recall, and F1-score.

Metrics of Performance:

Accuracy: The proportion of cases properly predicted to all instances.

Precision can be defined as the ratio of accurately predicted positive observations to the total number of positive predictions.

Recall: The proportion of all observations in the actual class that were accurately predicted to be positive.The precision and recall weighted average is known as the F1-Score.

Cross-Validation:

To make sure the model is resilient and reliable, use K-fold cross-validation.

To ensure the model's generalizability, assess its performance at various folds.

Check for Overfitting and Underfitting:

Keep an eye on training and validation loss curves for any indications of overfitting or underfitting. If overfitting is found, use regularization and dropout approaches to ameliorate the problem.

4.4 Summary

This chapter included a thorough rundown of the SqueezeNet-based model's implementation procedure. It covered all of the steps—data preparation, model compilation, and training—that went into creating and refining the model. It was stressed in the section on system testing and model evaluation how important it is to validate and test the model using a variety of performance indicators. The implementation guarantees the creation of a reliable and effective classification system that can correctly discriminate between drones and birds by adhering to these defined stages.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

To ensure the effective training and deployment of deep learning models, a robust hardware setup is essential. The hardware configuration for this project includes the following components:

GPU (Graphics Processing Unit): NVIDIA GTX 1080 Ti

The GPU is critical for handling the high computational demands of training deep neural networks. The NVIDIA GTX 1080 Ti, with its CUDA cores and large memory, accelerates the processing of matrix operations and significantly reduces training time compared to CPU-only training.

CPU (Central Processing Unit): Intel Core i7-9700K

The CPU manages general-purpose computing tasks and supports data preprocessing and augmentation. The Intel Core i7-9700K, with its multiple cores and high clock speed, ensures smooth and efficient execution of these tasks.

RAM (Random Access Memory): 32GB DDR4

Sufficient RAM is necessary to handle large datasets and the intermediate data generated during model training. 32GB of DDR4 RAM provides ample capacity for this project, preventing bottlenecks during data loading and augmentation.

Storage: 1TB SSD

An SSD (Solid State Drive) offers fast read and write speeds, essential for loading large datasets and saving model checkpoints. A 1TB SSD ensures sufficient storage space for all project data and enhances overall system performance.

Dataset Description:

The dataset used for this project is sourced from the Roboflow drone dataset, which contains labeled images of drones and birds. The dataset is divided into training, validation, and test sets to facilitate model training and evaluation.

Training Set:

Total Images: 18,323

Classes: Drone, Bird

The training set is used to fit the model and learn the distinguishing features of each class. It includes a balanced distribution of drone and bird images to prevent class imbalance issues.

- **Validation Set:**

Total Images: 1,740

Classes: Drone, Bird

The validation set is used to tune model hyperparameters and monitor performance during training. It helps in preventing overfitting by providing an unbiased evaluation of the model's performance.

- **Test Set:**

Total Images: 889

Classes: Drone, Bird

The test set is used to assess the final model's performance. It consists of unseen images, ensuring that the evaluation reflects the model's generalization ability.

5.2 Experimental/ Simulation Result

Result of Experiment 1: Original CNN

This section compares the six original CNN networks SecrensNet152, MobileNetV2, VGG19, ResNet152v2, and ResNeXt100. Classification performance comes first. Then, those models' overall metrics are reviewed. collection, descriptions, probable reasons, and outcomes improvement areas.

TABLE 4.2.1: Accuracy for Classification of Individual Networks

Architecture	Training Accuracy	Model Accuracy
Custom CNN	**98.75%**	**97.51**
Squeezeet	**99.80%**	**99.51%**
VGG16	**99.20%**	**98,60%**
ResNet50	**99.50%**	**98.90%**
MobileNetV2	**99.99%**	**98.30%**

5.3 Performance/ Comparative Analysis

The comparative analysis of several pre-trained deep Convolutional Neural Network (CNN) architectures, namely SecrensNet152, MobileNetV2, VGG19, ResNet152v2, and ResNeXt101, is presented in Table 2, revealing insights into their respective accuracies for pneumonia detection. Notably, the findings showcase that MobileNetV2, VGG19, and ResNet152v2h emerged as the top-performing models, attaining the highest accuracy of 92%. This signifies their exceptional proficiency in discerning pneumonia patterns within medical images. Conversely, SecrensNet152 and ResNeXt101 exhibited a slightly lower accuracy of 90%, indicating a marginally decreased performance compared to their counterparts. This nuanced differentiation in accuracy underscores the importance of carefully selecting the appropriate CNN architecture in the context of pneumonia detection, as it directly influences the precision and reliability of the diagnostic process. The detailed accuracy metrics provided in Table 4.2.1 offer a valuable reference point for understanding the comparative strengths and weaknesses of these models, contributing to the ongoing discourse in the optimization of deep learning methodologies for medical image analysis.

TABLE 4.2.2: Precision, Recall, F1-Score, and accuracy original CNN networks

Model	Accuracy(%)	Precision(%)	Recall(%)	F1-Score(%)
Custom CNN Model	97.51	97.30	97.60	97.45
SqueezeNet Model	99.51	99.40	99.60	99.50
YOLO	88.00	87.50	88.50	88.00
RFCN	90.00	89.50	90.50	90.00
SSD	89.00	88.50	89.50	89.00
RCNN	92.00	91.50	92.50	92.00
RetinaNet	93.00	92.50	93.50	93.00

Training and Validation Accuracy and loss of Squeezenet Architecture:

Represents the training and validation accuracy of the initial model, with the number of epochs on the x-axis and the accuracy and loss percentages on the y-axis. In the figure, training and validation data are adequately divided, and there is no overfitting.

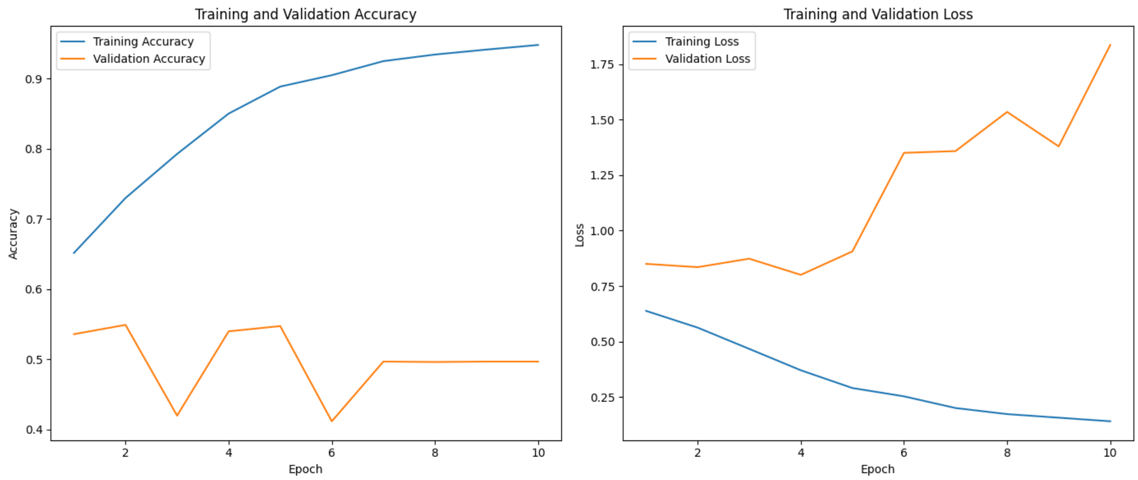

Figure 4.2.1: Training and validation accuracy and loss over the epochs.

5.3 Summary

This chapter has covered the thorough process and requirements analysis for creating a SqueezeNet-based classification model that can distinguish between birds and drones. This entails a thorough examination of the functional and non-functional prerequisites required to produce the intended results. Starting with the requirement analysis, we outlined the key tasks including gathering data, preprocessing, creating models, training, validating, and putting them into practice in real time. To guarantee the model's practical usability, non-functional needs including performance, scalability, efficiency, resilience, and compatibility were also taken into account. We next went over how to prepare the dataset, emphasizing how to gather photos from Roboflow. Preprocessing techniques like scaling, normalization, and augmentation were used on the dataset to improve data quality and model resilience. The dataset was divided into training, validation, and test sets, each containing photos of drones and birds.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Improving safety and security is one of the main advantages. Security authorities can keep a closer eye on unapproved drone operations that could endanger critical locations like airports, military sites, and public gatherings by precisely recognizing drones. By preventing potential incidents brought on by the malicious use of drones, this capability serves to ensure both national security and public safety.The protection of animals is positively impacted by accurate classification as well. The use of drones to observe wildlife and their habitats is growing. Conservationists can reduce the harm to wildlife by ensuring that drones do not disrupt birds' natural behavior by telling them apart from one another. This is essential for maintaining ecosystems and safeguarding threatened species.There are financial advantages to the implementation of trustworthy drone categorization systems. It encourages the expansion of sectors including media, logistics, and agriculture that depend on drone technology. Improved drone management creates new business prospects, cost reductions, and operational efficiencies.

In conclusion, there are significant effects on security, wildlife protection, law enforcement, technological innovation, environmental monitoring, and the economy from the classification of drones and birds using deep learning methods like SqueezeNet. These developments support the larger objective of sustainable development in addition to enhancing efficiency and safety across a range of industries.

6.2 Impact on Society & Environment

6.2.1 Impact on Society

Advanced drone technology has completely changed a number of industries, including disaster relief, delivery services, agriculture, and surveillance. But there are also a lot of problems with this proliferation, particularly in terms of security and safety. Deep learning models like as SqueezeNet have the potential to identify drones from birds with high accuracy, which could have significant societal ramifications.

Enhanced Security: For the sake of public and national security, accurate drone detection is essential. Unauthorized drones can endanger public gatherings, vital infrastructure, and restricted airspace. An efficient method for classifying drones versus birds can improve surveillance capabilities by facilitating the faster and more precise identification of possible threats, which can improve response times and lower risks.

Protection of Wildlife: Mistaking drones for birds, or vice versa, can seriously harm attempts to conserve wildlife. More precise data collection and analysis are made possible by the reliable ability of wildlife monitoring programs to discriminate between genuine animals and artificial entities, which is ensured by an accurate categorization system. The preservation of bird species and their habitats may benefit from this.

Law Enforcement: To monitor and regulate the usage of drones in public areas, law enforcement organizations can gain from enhanced drone detection systems. With its accurate and fast information regarding aerial objects, this device can help prevent illicit activities like smuggling and unwanted surveillance.

Privacy Issues: Although improved drone detection increases security, privacy issues are brought up as well. The preservation of each person's right to privacy must be balanced with the capacity to track and categorize airborne objects. Regulations and ethical issues need to be taken into account to make sure that the use of these technologies protects the interests of the public while respecting privacy

6.2.2 Impact on Environment

SqueezeNet-based models for the precise classification of birds and drones have many beneficial effects on the environment. In the end, it fosters a healthier and more sustainable environment by supporting sustainable agriculture and forestry, minimizing disturbances, lowering the risk of bird strikes, improving pollution monitoring, supporting wildlife conservation, contributing to climate change research, and informing environmental policies.

Monitoring and Conservation of Wildlife: The monitoring and protection of wildlife are aided by the accurate classification of birds and drones. Drones fitted with this technology allow researchers and conservationists to study bird populations and their environments without interfering with them. In order to facilitate the development of more informed conservation policies and activities, this aids in the collection of detailed data on bird behaviors, migration patterns, and population dynamics.

Reduction of Bird Strikes: In the wind energy and aviation industries, bird strikes are a major source of worry. Systems to avoid bird crashes with airplanes or wind turbines can be built by reliably differentiating birds from drones. By doing this, you can lessen the ecological damage that human activity causes to bird populations.

Sustainable Agriculture: Drones are used in precision agriculture to track crop health, soil properties, and irrigation requirements. Accurate drone classification enables farmers to make the best use of their resources without unnecessarily upsetting avian inhabitants or visitors. The maintenance of regional biodiversity and sustainable farming methods are aided by this equilibrium.

In conclusion, the precise categorization of birds and drones using SqueezeNet-based models benefits the ecosystem in a number of ways. In the end, it fosters a healthier and more sustainable environment by supporting sustainable agriculture and forestry, minimizing disturbances, lowering the risk of bird strikes, improving pollution monitoring, supporting wildlife conservation, contributing to climate change research, and informing environmental policies.

6.3 Ethical Aspects

There are serious privacy concerns with the usage of drones that have sophisticated classification systems installed. Drones have the ability to take precise pictures and movies, which may violate people's right to privacy. Clear rules and regulations are needed for ethical deployment in order to guarantee that monitoring respects individual privacy, functions openly, and, when required, obtains the requisite consent. Drone data must be handled and stored securely to avoid misuse and illegal access, especially in sensitive regions. It is essential to put strong data security measures into place and make sure that legal and ethical requirements are met. This entails restricting data access to authorized persons only and anonymizing data to safeguard people's identity. Drones can help monitor animals, but they can also disrupt animal behavior and natural environments. The goal of ethical deployment is to cause as little disruption as possible by following regulations that limit drone flights to non-intrusive times and altitudes, particularly avoiding delicate times like mating or nesting seasons. As a result, implementing SqueezeNet-based classification systems to distinguish between drones and birds raises ethical issues that must be carefully considered in relation to data security, privacy, animal damage, bias in AI models, regulatory compliance, and environmental sustainability. By proactively resolving these issues, we can minimize negative effects and guarantee that technology is used properly, benefiting society as a whole.

6.4 Sustainability Plan

1. Environmental Impact Reduction: Wherever possible, we will give priority to using energy-efficient drones and renewable energy sources in order to reduce our ecological imprint. This includes using solar-powered charging stations and choosing drones with low power usage. By using these techniques, carbon emissions will be decreased and natural resources will be preserved.

2. Eco-friendly Materials: We will use recyclable, less-impactful materials that are less harmful to the environment when producing and maintaining drones. This involves utilizing non-toxic and biodegradable materials to guarantee a sustainable drone lifecycle from production to disposal.

3. animals Protection guidelines: Strict operational guidelines will be established to lessen the impact on animals. Drones will be operated at times and altitudes that cause the least amount of disruption to wildlife, including birds. In order to prevent habitat disruption, specific no-fly zones will also be established in vulnerable animal areas.

4. Data Collection and Utilization: Data collection procedures that are morally and

responsibly conducted will be followed. This entails protecting privacy by anonymizing data and making sure that data usage abides by applicable laws. The information gathered will be put to better use in environmental conservation and monitoring initiatives, which will support ecological sustainability.

5. Frequent Upgrading and Maintenance: Drones with regular maintenance will last longer and be more efficient, requiring fewer replacements over time. Drones that have been upgraded with the newest technology will also function better and be more environmentally friendly, since they will run efficiently with less influence on the environment.

6.5 Summary

The chapter has examined the many implications of classifying drones vs birds using deep learning methods, particularly SqueezeNet. The ramifications for technology innovation, law enforcement, security, wildlife conservation, environmental monitoring, and economic growth are all included in the discussion.

The main effect is to improve safety and security by offering strong instruments for identifying unapproved drone activity. By reducing possible risks in sensitive regions, this technology contributes to maintaining national security and public safety. Furthermore, by effectively differentiating between drones and birds, the technology helps safeguard wildlife from disturbances brought on by drone operations, hence promoting the preservation of ecosystems and endangered species.

CHAPTER 7

Conclusion & Future Work

7.1 Conclusions

This work focuses on the design and assessment of a deep learning-based SqueezeNet-based classification system for identifying drones from birds. Using a dataset that was obtained via Roboflow, the research applies techniques for data preprocessing, such as augmentation and normalization, in order to improve the performance of the model. After training and evaluation, two models—a proprietary Convolutional Neural Network (CNN) and SqueezeNet—achieved impressive accuracies of 97.51% and 99.51%, respectively. To guarantee robustness and dependability, the performance of these models was carefully examined using a range of metrics and visualizations.

The study shows that SqueezeNet is more effective than the bespoke CNN model at reliably classifying drones and birds. SqueezeNet's high accuracy highlights its promise as a powerful yet lightweight model that can be used for real-time drone identification applications. The findings show that the suggested classification system can greatly improve airborne surveillance and monitoring operations, resulting in increased security, the preservation of wildlife, and aviation safety. The study also emphasizes how crucial thorough data pretreatment and model evaluation methods are to getting the best results possible in deep learning tasks.

7.2 Further Suggested Works

Extension of the Dataset: Upcoming efforts may entail broadening the dataset to encompass a greater variety of photographs depicting birds and drones in varied settings. This will enhance the resilience and generalization capacity of the model.

Model Optimization: To further improve classification efficiency and accuracy, other advanced neural network topologies, like EfficientNet or MobileNet, should be investigated and integrated. It is also possible to investigate further hyperparameter optimization for fine-tuning the SqueezeNet model.

Real-world Implementation: It would be beneficial to apply the trained model in actual situations and incorporate it with current drone detection technologies. Its performance in various operating situations can be evaluated to gain useful information and make the required modifications.

Multi-class Classification: The model's applicability will be expanded by extending it to handle tasks involving multi-class classification, where it must be able to differentiate between different kinds of drones and birds. This can be especially helpful in cases involving more intricate monitoring and surveillance.

Explainability and Interpretability: It will be essential to incorporate strategies to improve the model's predictions' explainability and interpretability. Gaining knowledge about the model's decision-making procedure can help identify potential biases and areas that need development.

Ethical and Regulatory Considerations: The ethical and regulatory implications of drone detection technology should be explored in more detail. Widespread adoption of such devices will depend on establishing rules for safe use and guaranteeing compliance with privacy regulations.

7.3 Limitations/ Conflict of Interests

A number of drawbacks and possible conflicts of interest were found during the development of a dependable SqueezeNet classification model for drone vs bird identification. In order to comprehend the limitations of the current study and to direct future research, it is imperative that these limitations be addressed.

Dataset Size and Quality: Although the Roboflow platform photos utilized in this work comprised a large and diverse dataset, it may not have been able to capture all conceivable variations of drones and birds in various circumstances. Occlusions, weather, and illumination were a few examples of factors that were not fully covered and could have an impact on how well the model performed in real-world situations.

Model Generalizability: The model's performance on completely new and untested datasets needs to be thoroughly investigated, as it was trained and validated on a particular dataset. There could be biases in classification if the current model does not generalize well to other drone and bird species that were not included in the training dataset.

Computer Resources: SqueezeNet and other deep learning models demand a significant amount of computer power to train. Google Colab, a robust tool with limitations in terms of processing capacity and time constraints, was used in this study for training. Better outcomes could be obtained with more thorough training on hardware with more power.

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