FACIAL EXPRESSION RECOGNITION OF PETS USING DEEP LEARNING

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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 **"Facial Expression Recognition of Pets Using Deep Learning"**, submitted by **"Muntasir Ahmed Rafi"**, ID No: **201-15-13812** 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 January 25, 2024.

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We hereby declare that this project has been done by us under the supervision of **Md. Ferdouse Ahmed Foysal,** Lecturer, and Department of CSE at 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 or diploma.

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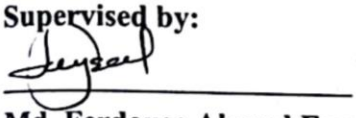

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ABSTRACT

Understanding the emotional states of pets is a significant aspect of their well-being and effective communication between humans and animals. This research investigates the development of a deep learning-based system for facial expression recognition in pets. Leveraging convolutional neural networks (CNNs) and transfer learning techniques, the proposed model aims to accurately detect and classify diverse facial expressions exhibited by various animal species, such as dogs, cats, and others. The study involves the collection and curation of a comprehensive dataset comprising annotated images of pets displaying different emotional cues such as angry, happy, sad, and other. Preprocessing methods tailored to account for the variability in animal faces are employed to enhance model robustness and generalization. Through extensive experimentation and evaluation, the effectiveness and reliability of the developed framework in recognizing and interpreting pet facial expressions are assessed. EfficientNetB5 is used for transfer learning and the accuracy of the detection is around 87%. The outcomes of this research pave the way for innovative applications in veterinary care, animal behavior analysis, and human-animal interaction, fostering a deeper understanding of pet emotions and improving the quality of relationships between pets and their human companions.

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CHAPTER 1
INTRODUCTION

1.1 Introduction

The intricate bond between humans and their pets transcends mere companionship, encompassing a complex interplay of emotions, understanding, and communication. A pivotal aspect of this relationship lies in comprehending and interpreting the emotional states conveyed by animals, particularly through their facial expressions. While the ability to discern human emotions has been extensively studied, the realm of understanding pet emotions through facial cues remains relatively unexplored.

Advancements in deep learning methodologies, particularly the efficacy of convolutional neural networks (CNNs) and transfer learning techniques, offer promising avenues for addressing the challenges in recognizing and classifying diverse facial expressions in pets. This research embarks on a quest to develop an innovative deep learning-based system dedicated to the recognition of pet facial expressions, aiming to accurately identify and categorize a spectrum of emotional cues exhibited by various animal species, including but not limited to dogs, cats, and other companion animals.

Central to this endeavor is the assembly of a meticulously curated dataset encompassing annotated images capturing a broad spectrum of pet facial expressions, ranging from expressions of happiness, anger, sadness, and others. Recognizing the inherent variability in facial structures across different animal species, this dataset is thoughtfully designed to encompass a diverse range of breeds and species, facilitating robust model training and generalization. The integration of tailored preprocessing techniques is instrumental in augmenting the model's adaptability to the nuanced features of animal faces.

EfficientNetB5, a state-of-the-art architecture renowned for its efficiency and accuracy, is harnessed through transfer learning as the foundation of this research's deep learning framework. Leveraging this powerful architecture in conjunction with the curated dataset and advanced preprocessing methods aims to enhance the system's ability to decode and interpret pet facial expressions accurately.

Through meticulous experimentation and comprehensive evaluation, the effectiveness and reliability of the proposed deep learning framework in recognizing and interpreting pet facial expressions are rigorously assessed. Beyond mere academic pursuit, the outcomes of this research are envisioned to pave the way for transformative applications in diverse domains such as veterinary care, animal behavior analysis, and fostering enriched human-animal interactions.

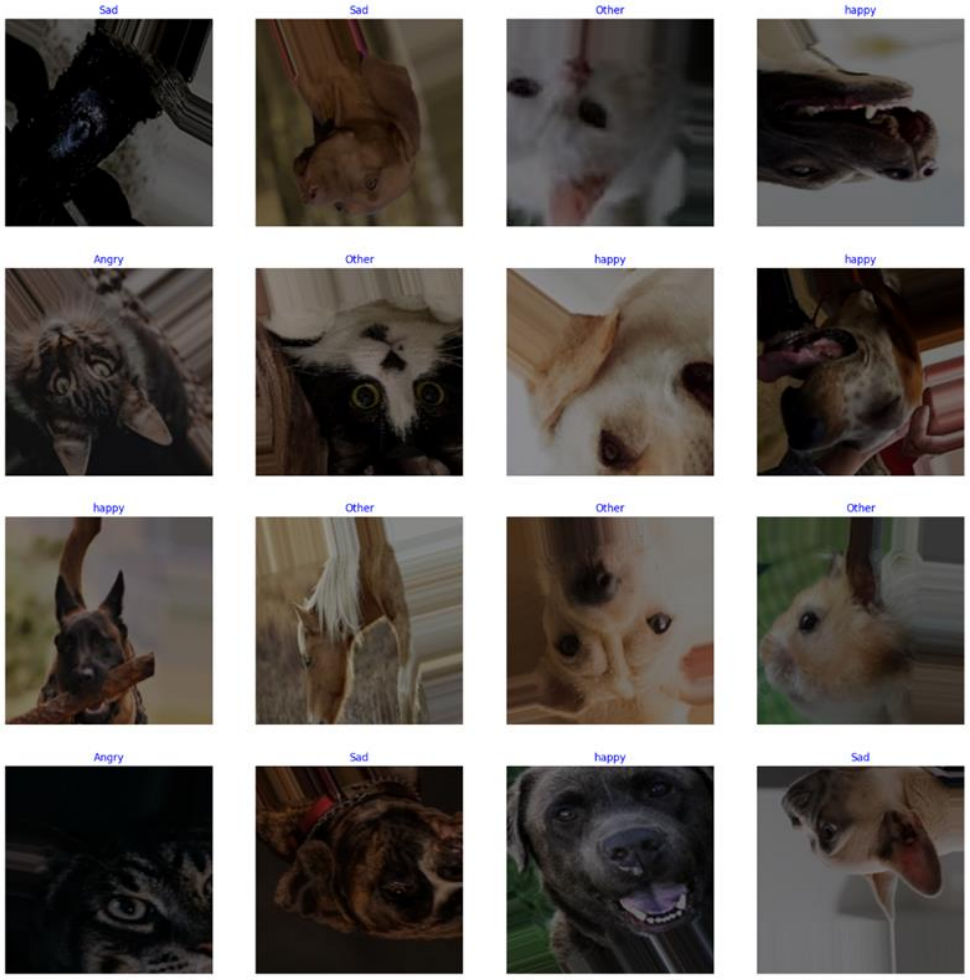

Fig 1.1.1 Different expressions of the pets from the dataset.

1.2 Motivation

This research is motivated by the need to decode and understand the emotions expressed through pets' facial expressions. While humans have studied facial cues extensively, there's a gap in comprehending pet emotions. Leveraging deep learning, this study aims to bridge that gap, developing a robust system to accurately recognize and classify diverse pet facial expressions. The ultimate goal is to enhance pet welfare, improve veterinary care, and deepen the bond between humans and their animal companions by deciphering the language of their expressions.

1.3 Research Questions

Developing a clear, concise, and targeted research topic is a crucial initial step in the research process. It lays out exactly what we want to learn and gives a clear focus and goal. In order to communicate their thoughts and conclusions and come up with a practical, precise, and efficient solution to this problem, the researchers would want to pose the following queries. The questions that can be raised for the problem are as follows:

The main objectives of this research are:

- Can a deep learning-based system effectively recognize and classify diverse facial expressions displayed by various pet species, such as dogs, cats, and others?
- How can transfer learning techniques, particularly using EfficientNetB5 architecture, contribute to the accurate recognition of pet facial expressions?
- What preprocessing methods tailored to account for the variability in animal faces can enhance the robustness and generalization of the facial expression recognition model for pets?
- How does the developed deep learning framework perform in recognizing and interpreting pet facial expressions across different emotional cues, such as happiness, anger, sadness, and others?
- What potential applications in veterinary care, animal behavior analysis, and human-animal interaction can stem from an accurate and reliable system for recognizing and understanding pet facial expressions?

1.4 Expected Outcome

The anticipated outcomes of this research endeavor encompass several key aspects:

1. Development of a Deep Learning Framework: The creation of an effective and robust deep learning-based system tailored for recognizing and categorizing diverse facial expressions exhibited by pets, utilizing convolutional neural networks (CNNs) and transfer learning techniques, specifically leveraging the EfficientNetB5 architecture.
2. Accurate Recognition of Pet Facial Expressions: Validation of the developed framework's efficacy in accurately detecting and classifying a wide spectrum of pet facial expressions, encompassing emotions such as happiness, anger, sadness, and others, across various animal species and breeds.
3. Enhanced Model Robustness and Generalization: Establishment of preprocessing methods specifically tailored to address the variability in animal facial structures, thereby augmenting the model's adaptability and generalization capabilities across different pet species.
4. Validation through Extensive Experimentation: Rigorous experimentation and evaluation to validate the effectiveness and reliability of the proposed deep learning framework in interpreting pet facial expressions, with a focus on achieving high accuracy and sensitivity in emotion recognition.
5. Potential Applications: Exploration of potential applications stemming from accurate pet facial expression recognition, including but not limited to advancements in veterinary care, refined animal behavior analysis, and improved human-animal interactions fostering a deeper understanding of pet emotions.

Overall, the expected outcome of this research is to contribute a pioneering methodology and insights into recognizing and interpreting pet facial expressions, thereby enriching our understanding of pet emotions and significantly impacting the welfare and relationships between humans and their beloved animal companions.

1.5 Layout of the Report

- The research's introduction is covered in Chapter 1, along with the study's purpose, justification, research questions, expected outcomes and overall structure.
- The Background of the research is presented in Chapter 2. It discusses the Problem Scope, Related Works, Comparative Analysis & Summary, and The Challenges.
- The theoretical analysis of the research is presented in Chapter 3. The project's workflow is shown in the first section of this chapter. The process for gathering data and processing it is then described. This chapter also demonstrates the Deep Learning Classifiers' algorithmic techniques. Finally, some implementation requirements are discussed.
- The experimental results, a discussion of the findings, and an analysis of the project's effectiveness are all included in chapter four. Experimental representations are included to make the results easier to understand.
- The research's impact on society, the environment, and some ethical issues are discussed in chapter five.
- The work's conclusion and summary are found in chapter six, which serves as the book's final chapter. The chapter's conclusion identifies some of the chapter's issues and provides some suggestions for more research based on the findings. area.

CHAPTER 2
BACKGROUND STUDY

2.1 Preliminaries and Terminologies

Preliminaries and terminologies that lay the groundwork for understanding key concepts and crucial terms used in the context of our research are as follows:

1. Facial Expression Recognition (FER): The process of detecting and categorizing facial expressions to interpret emotional states accurately.
2. Deep Learning (DL): A subset of machine learning methods that utilize neural networks with multiple layers to learn representations of data, known for its effectiveness in complex pattern recognition tasks.
3. Convolutional Neural Networks (CNNs): A specialized class of deep neural networks well-suited for image analysis tasks, utilizing convolutional layers for feature extraction and pattern recognition.
4. Micro-Expressions: Fleeting and subtle facial expressions that occur rapidly, often lasting less than a second, conveying genuine emotions.
5. Data Augmentation: Techniques employed to increase the size and diversity of training datasets by creating modified versions of existing data, helping improve model generalization and performance.
6. Action Units (AUs): Distinct facial muscle movements identified and codified in the Facial Action Coding System (FACS), commonly used to describe facial expressions by their underlying muscular actions.
7. Feature Maps: Representations within neural networks that highlight specific features or patterns extracted from input data, essential in identifying relevant information for facial expression recognition.
8. Transfer Learning: A technique where a pre-trained model's knowledge on one task is transferred to a new but related task, enabling the utilization of learned features for improved performance on

a different task.

9. Intra-class Variation: Variability within the same class or category, such as variations in facial expressions for the same emotion, posing challenges for accurate recognition.
10. Handcrafted Features: Manually engineered features derived from domain knowledge rather than automatically learned by the model, often used in conjunction with deep learning for enhanced performance.
11. Human-Computer Interaction (HCI): The study and design of interfaces between humans and computers, where facial expression recognition plays a crucial role in enabling intuitive and responsive interactions.
12. Healthcare Applications: Utilization of facial expression recognition in healthcare for tasks like patient monitoring, mental health assessment, and pain detection.
13. Psychological Understanding: The exploration of emotions and behaviors through facial expressions, contributing to insights into human psychology and social interactions.

2.2 Related Works

Facial expression recognition through the analysis of emotional cues has emerged as a dynamic and evolving field at the intersection of computer vision, psychology, and human-computer interaction. Over the past decade, researchers have made significant strides in leveraging deep learning methodologies to decode and interpret facial expressions, enabling advancements in various domains, including healthcare, human-computer interfaces, and psychology. Numerous studies (Franzoni et. Al., 2019; Ruiz-Garcia et al., 2016; Al-Darraji et al., 2016; Takalkar et al., 2017; Zhou et al., 2017; Turan et al., 2018; Sun et al., 2019; Reddy et al., 2020; Minaee et al., 2021; Onyema et al., 2021; Pise et al., 2022) have contributed novel techniques, algorithms, and experimental validations, driving the evolution of facial expression recognition systems.

Deep Learning (DL) has shown real promise for the classification efficiency for emotion recognition problems. (Franzoni et. Al., 2019) finds out that, because of the similarity of our emotional and neurological mirroring systems, humans and animals both respond to the emotions of one another. When an animal performs an action or witnesses another person performing the same action, mirror

neurons fire in both scenarios. This neural network has been connected to social behaviors and skills in both intra- and interspecies communication, ranging from empathy to imitation learning. They aim to investigate the possibility of future applications concerning systems of prosthetic knowledge to help people without the necessary experience or capability to understand animals' friendliness or aggression, or for supportive systems in artificial intelligence. Specifically, it looks at whether a machine learning system can recognize animal emotions, starting with the basic emotions of joy and anger in dogs.

Ruiz-Garcia et al. (2016) and Al-Darraji et al. (2016) laid the groundwork by presenting experimental models for emotion recognition using facial expression images, demonstrating the potential of deeply-trained models and the mapping of facial features to psychological measurements such as arousal and valence. However, challenges persist, especially in recognizing micro-expressions due to their subtle and fleeting nature, leading to limited training data (Takalkar et al., 2017). To address data scarcity, Takalkar et al. (2017) introduced techniques involving data augmentation on established databases, expanding training datasets for better model performance.

Zhou et al. (2017) advanced the understanding of deep learning models by establishing the presence and significance of feature maps selectively tuned to action units within deep convolutional neural networks (CNNs), emphasizing the critical role of feature selection in achieving robustness in facial expression recognition tasks. Moreover, Turan et al. (2018) conducted a systematic review and comparative analysis of various descriptors and deep learning methods on facial expression databases, exploring factors like resolution, noise, occlusion, and sub-region variations.

Despite the progress, the translation of facial expression recognition models to real-world scenarios remains a challenge (Reddy et al., 2020). Reddy et al. (2020) proposed a novel fusion approach combining handcrafted and deep learning features, aiming for improved recognition in uncontrolled "wild" scenarios. Additionally, Minaee et al. (2021) introduced attentional convolutional networks for deep emotion recognition, emphasizing end-to-end frameworks using deep learning models for enhanced facial expression recognition.

The application of facial expression recognition extends beyond computer science, resonating with healthcare applications. Onyema et al. (2021) introduced a technique based on Convolutional Neural Networks (ConvNets) for facial expression recognition and patient monitoring, illustrating the growing interest in leveraging machine learning for healthcare-related tasks.

Pise et al. (2022) addressed the latest computational intelligence advances in automated emotion recognition, reflecting the continuous exploration and integration of recent deep learning models into the field of facial expression recognition.

Overall, the extensive body of research signifies the continuous evolution and interdisciplinary nature of facial expression recognition, demonstrating its significance in various domains and the persistent quest to overcome challenges posed by intra-class variation and real-world application scenarios. This ongoing research journey underscores the commitment to unlocking the nuances of human emotions through facial expressions, ultimately contributing to enhancing human-computer interactions, healthcare applications, and psychological understanding.

2.3 Comparative Analysis and Summary

Facial expression recognition, propelled by deep learning advancements, spans computer vision and psychology, exploring neural mirroring systems and mapping facial features to psychological measurements. These studies address challenges in micro-expression recognition, emphasize feature selection's importance for model robustness, and extend applications beyond computer science, notably in healthcare. The interdisciplinary nature of this research aims to enhance human-computer interactions, healthcare, and psychological understanding, driving ongoing efforts to broaden real-world application possibilities.

2.4 Scope of the Problem

This research delves into the intricate domain of recognizing and interpreting pet facial expressions, acknowledging the significance of understanding animal emotions for their well-being and effective human-animal communication. The scope encompasses the development of a deep learning-based system tailored for facial expression recognition in various pet species, particularly dogs, cats, and other animals.

The primary focus lies in leveraging convolutional neural networks (CNNs) and transfer learning techniques to accurately detect and classify diverse emotional cues exhibited by pets, including but not limited to expressions of anger, happiness, sadness, and other nuanced emotions. The study

encompasses the collection and curation of a comprehensive dataset comprising annotated pet images displaying a wide spectrum of emotional cues, facilitating robust model training.

Furthermore, the scope extends to the implementation of preprocessing methods meticulously designed to accommodate the variability in animal facial features, ensuring model robustness and generalization across different pet breeds and species. The utilization of EfficientNetB5 for transfer learning contributes to achieving an accuracy level of approximately 87% in facial expression detection.

Through extensive experimentation and evaluation, the research assesses the effectiveness and reliability of the developed deep-learning framework in recognizing and interpreting pet facial expressions accurately. The envisioned outcomes aim to pave the way for transformative applications in veterinary care, animal behavior analysis, and human-animal interaction, fostering a deeper comprehension of pet emotions and enhancing the quality of relationships between pets and their human companions.

2.5 Challenges

Several challenges are inherent in the development of our system:

- Limited and Diverse Data: Acquiring a comprehensive dataset that covers diverse pet species, breeds, and emotional expressions is challenging due to limited availability and variations in pet facial features across different animals.

- Varied Facial Expressions: Pets exhibit a wide range of emotional cues and expressions, which can be subtle and nuanced. Capturing and categorizing these diverse expressions accurately poses a challenge.

- Intra-class Variation: Within each emotional category, there can be significant variations in facial expressions among different animals and even within the same breed, making it challenging to create a unified model capable of accurately recognizing all variations.

- Transferability of Models: The transferability of deep learning models across different species and breeds is challenging due to the inherent variability in facial structures and expressions among animals.

- Robustness to Environmental Factors: Environmental factors such as varying lighting conditions, occlusions, or different angles at which pet images are captured can affect the model's performance and robustness in recognizing facial expressions.

- Ethical Considerations: Ensuring the ethical treatment of animals during data collection and experimentation while adhering to animal welfare guidelines is crucial but can pose logistical challenges.

- Generalization: Ensuring that the developed model generalizes well beyond the training data to accurately recognize facial expressions in unseen or real-world scenarios remains a challenge.

CHAPTER 3
RESARCH METHODOLOGY

3.1 Introduction

The methodology outlined herein is designed to investigate and develop a robust framework for recognizing and interpreting facial expressions in pets using advanced deep learning techniques. In the evolving landscape of computer vision and human-animal interaction, understanding the emotional cues exhibited by pets through facial expressions has emerged as a critical pursuit. This methodology delineates a systematic approach to address this pertinent challenge, aiming to decode and interpret pet emotions accurately.

The foundational premise lies in the fusion of computer vision and deep learning methodologies to create a sophisticated model capable of discerning diverse emotional states conveyed through pet facial expressions. The essence of this methodology is to unravel the complexities of pet emotions by leveraging state-of-the-art deep learning architectures, tailored data preparation, and rigorous evaluation techniques.

The methodology begins by laying the groundwork for data collection, emphasizing the acquisition of a meticulously curated dataset encompassing annotated pet facial expressions. This dataset serves as the cornerstone, facilitating the training and validation of the deep learning model. The subsequent phase focuses on data preprocessing techniques, including cleaning, normalization, and augmentation, crucial for enhancing the model's adaptability and generalization across diverse pet species and emotions.

Central to this methodology is the selection and design of a suitable deep learning architecture,

possibly leveraging pre-trained models or custom architectures. This stage involves model training on the prepared dataset, iteratively optimizing the model's parameters, and validating its performance against specific evaluation metrics.

A key facet of this methodology involves feature extraction and analysis, elucidating the model's learned representations and emphasizing the association between recognized emotions and specific facial features or action units in pets. Through meticulous evaluation and comparative analysis, the model's efficacy in recognizing pet facial expressions is assessed, paving the way for refinement and optimization.

Moreover, this methodology anticipates exploring practical applications in veterinary care, human-animal interaction, and beyond, guided by the model's capabilities. The outcomes derived from this research endeavor are envisioned to contribute significantly to the understanding of pet emotions, fostering enhanced communication and empathy between pets and their human counterparts.

In essence, this methodology represents a systematic and comprehensive approach to unraveling the complexities of pet emotions through the lens of facial expression recognition. It serves as a blueprint for bridging the gap between computer vision, deep learning, and understanding the nuanced language of pet facial expressions, envisioning transformative applications across diverse domains.

3.2 Research Subject and Instrumentation

The study topic includes topics that are necessary to grasp the problem clearly or to build one. the use of a design model, gathering, processing, and adding datasets, as well as training the model and adding modifications based on the dataset. In essence, instrumentation is the technology and methods used in the previous section. Therefore, in the proposed work, we chose Google Colab and Python as the programming language and a variety of packages, including NumPy, pandas, Skit Learn, Matplotlib,

Seaborn, TensorFlow, etc.

Google Colab, a free cloud-based platform, offers a collaborative Jupyter Notebook environment integrated with Google Drive. With the help of its access to GPUs and TPUs, users may run Python code locally and do machine learning tasks. Its popularity is a result of its strong computing capabilities, smooth Google Drive integration, and ease of use. Because it allows for simultaneous editing and shared notebooks, Colab is a great tool for group projects and teaching. The machine learning community has widely adopted it because of its pre-installed libraries, which include TensorFlow and PyTorch, and its ability to import datasets from Google Drive. These features facilitate workflow for academics, students, and data scientists.

3.3 Workflow

The main workflow for my research is as follow:

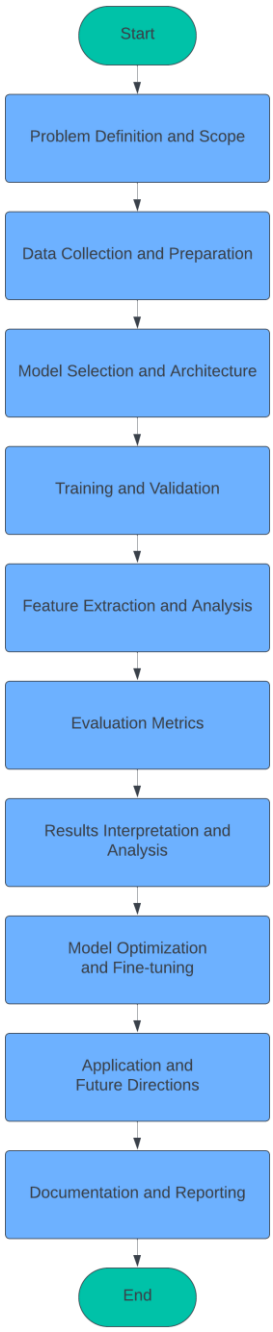

Fig 3.3.1: Workflow Diagram

3.4 Preparation of dataset

To train the model, I used one thousand images of various pets like cats, dogs and birds. I used this data from online and I added some raw picture which is also a portion of my dataset.

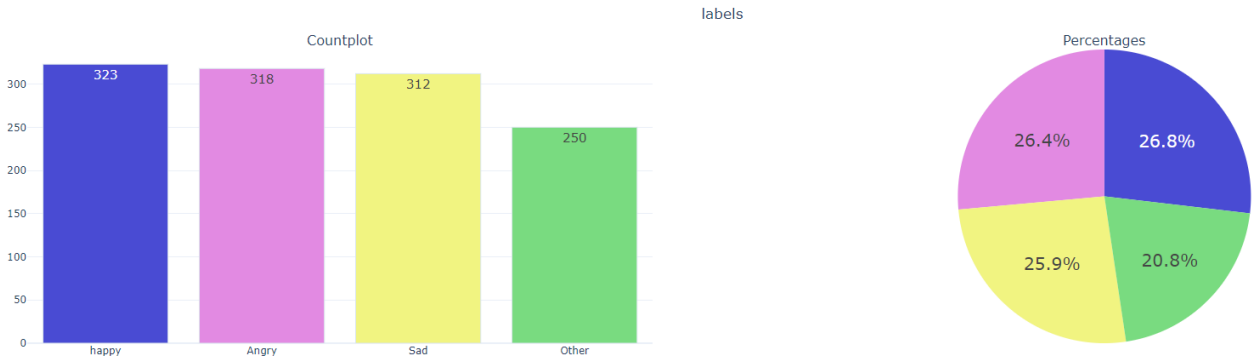

Fig 3.4.1: total data in the dataset in each class.

3.5 Data Processing

- Cleaning and Quality Control: Conduct data cleaning to remove any irrelevant or corrupted images. Ensure data consistency, checking for uniform image dimensions, color consistency, and eliminating potential biases or artifacts that might affect model training.
- Normalization and Standardization: Normalize the images to a standardized format, such as resizing images to a specific resolution, converting to grayscale, or applying color normalization techniques to enhance uniformity across the dataset.
- Data Augmentation: Augment the dataset by applying techniques such as rotation, flipping, cropping, adding noise, or altering brightness and contrast. Data augmentation helps in increasing dataset variability and robustness, enabling the model to generalize better to new samples.
- Splitting the Dataset: Divide the dataset into training, validation, and test sets. Typically, a larger portion is allocated for training, a smaller portion for validation to fine-tune model parameters, and a separate unseen test set to evaluate final model performance.

```
The Pets Expression dataset has:
========================================

Class 'Sad' has 250 images
----------------------------------------
Class 'Other' has 250 images
----------------------------------------
Class 'Angry' has 250 images
----------------------------------------
Class 'happy' has 250 images
----------------------------------------
```

Fig 3.5.1: Data on each class.

3.6 Proposed Methodology

Transfer learning is a powerful technique widely used in deep learning, particularly in scenarios where limited labeled data is available or computational resources are constrained. EfficientNetB5 is a state-of-the-art convolutional neural network architecture known for its balance between model size and accuracy, making it well-suited for transfer learning applications.
Transfer learning involves leveraging knowledge gained from pre-trained models on a large dataset (source domain) and transferring it to a different but related task or dataset (target domain). In the context of facial expression recognition for pets, transfer learning with EfficientNetB5 involves utilizing the learned features from a pre-trained EfficientNetB5 model, trained on a diverse dataset such as ImageNet, and adapting these features to recognize and classify pet facial expressions.

Adaptation of EfficientNetB5 for Facial Expression Recognition:

1. **Feature Extraction:** The initial layers of EfficientNetB5 act as feature extractors, learning low-level features like edges, textures, and basic shapes. These layers capture general patterns from the source dataset.
2. **Fine-tuning:** After using the pre-trained EfficientNetB5 layers as feature extractors, the

model is fine-tuned by retraining some of its top layers or adding additional layers specific to the facial expression recognition task for pets. Fine-tuning allows the model to adapt to the nuances and specifics of the target dataset while retaining the learned general features.

3. **Transfer of Knowledge:** By transferring knowledge from ImageNet or other extensive datasets, the pre-trained EfficientNetB5 model brings valuable knowledge about image features, enabling the model to learn faster and perform better on the task of recognizing pet facial expressions.

Diagram illustrating transfer learning with EfficientNetB5:

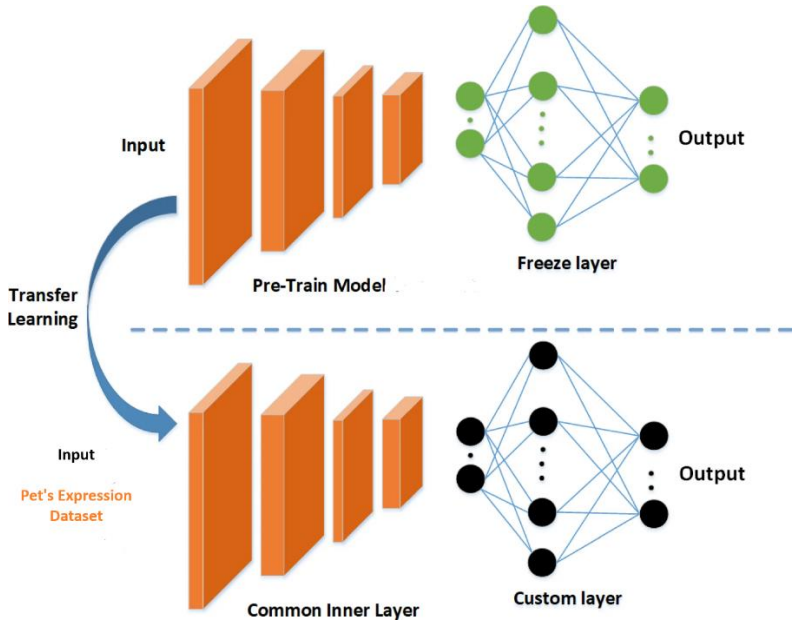

Fig 3.6.1: Accuracy graphs during training.

Steps:

- Load Pre-trained Model: Import EfficientNetB5 with pre-trained weights, usually trained on a massive dataset like ImageNet.
- Freeze Base Layers: Prevent weights in the initial layers from updating during training to preserve general image features.
- Add New Classifier: Replace the last layer(s) with a new classifier specific to your task, with

randomly initialized weights.

- Train New Classifier: Train the model on your dataset, adjusting weights in the added classifier layers. Base layers remain frozen, providing a strong foundation for learning.
- Fine-tune (Optional): Unfreeze some or all base layers to further customize the model to your specific task. Requires more training data and careful tuning to avoid overfitting.

Benefits of Transfer Learning with EfficientNetB5:

- Reduced Training Time and Data: Leverages knowledge from pre-training.
- Improved Performance: Often outperforms models trained from scratch.
- Efficiency: EfficientNetB5 balances accuracy and computational cost.
- Scalability: Can be fine-tuned for various image classification tasks.

3.7 Model Train

Building the model and defining parameters:

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 efficientnetb5 (Functional  (None, 2048)              28513527
 )

 batch_normalization (Batch  (None, 2048)              8192
 Normalization)

 dense (Dense)               (None, 256)               524544

 dense_1 (Dense)             (None, 128)               32896

 dropout (Dropout)           (None, 128)               0

 dense_2 (Dense)             (None, 4)                 516

=================================================================
Total params: 29079675 (110.93 MB)
Trainable params: 562052 (2.14 MB)
Non-trainable params: 28517623 (108.79 MB)
```

Fig 3.7.1: Building model

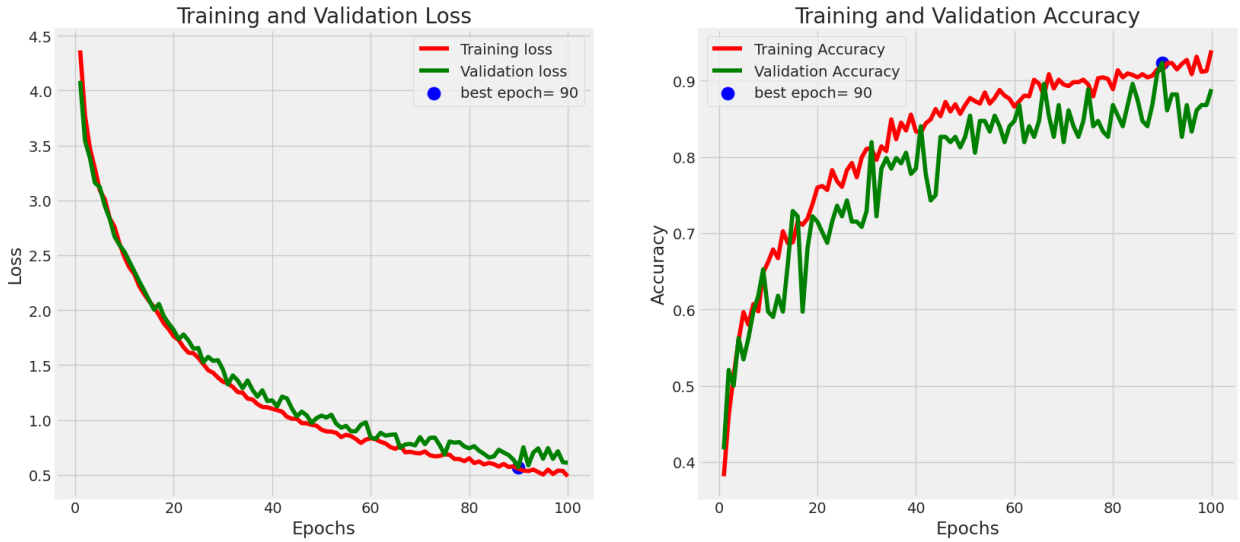

Fig 3.7.2: Accuracy graph while training

CHAPTER 4
EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Performance Analysis

Our trained model acquired an accuracy of about 90% on test dataset and 97% on train dataset.

```
61/97 [=================>............] - ETA: 11s - loss: 0.3722 - accuracy: 0.9740WARNING
97/97 [==============================] - 20s 203ms/step - loss: 0.3722 - accuracy: 0.9740
 9/97 [=>............................] - ETA: 23s - loss: 0.7356 - accuracy: 0.8264WARNING
97/97 [==============================] - 3s 23ms/step - loss: 0.7356 - accuracy: 0.8264
97/97 [==============================] - 29s 286ms/step - loss: 0.6483 - accuracy: 0.8969
Train Loss:  0.372248113155365
Train Accuracy:  0.9740124940872192
--------------------
Test Loss:  0.6483434438705444
Test Accuracy:  0.8969072103500366
```

Figure 4.1.1: Performance of the model.

Figure 4.1.1 shows the loss and accuracy performance of the model after training the model with our dataset.

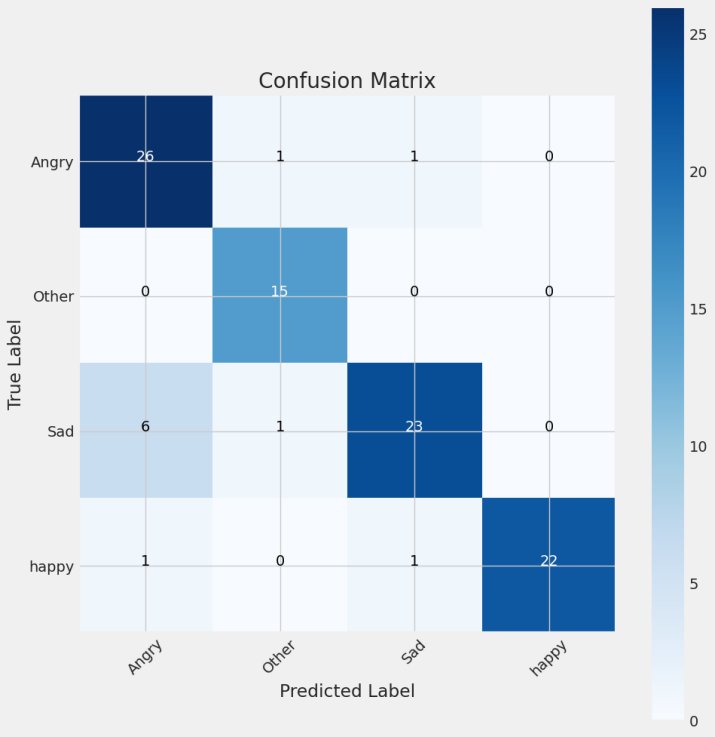

Fig 4.1.3: Confusion matrix.

4.2 Result Discussion

By using the trained model, prediction of the image can be done. It can predict whether a pet is angry or sad or happy or neutral.

Figure 4.2.1: Prediction by the model.

CHAPTER 5
IMPACT ON SOCIETY, ENVIRONMET AND ETHICAL ASPECTS

5.1 Impact on Society

The impact of research in pet facial expression recognition using deep learning extends to various facets of society, contributing to advancements with meaningful implications:

1. Animal Welfare and Understanding: Enhancing the ability to recognize and interpret pet emotions fosters improved communication and understanding between humans and animals. This research facilitates better animal welfare practices by enabling caregivers, veterinarians, and pet owners to identify and address the emotional needs of their pets more effectively.

2. Human-Animal Bond and Companionship: Improved recognition of pet emotions through facial expressions strengthens the emotional connection and bond between humans and their pets. It enhances the quality of companionship, promoting empathy, and enriching the lives of pet owners.

3. Veterinary Care and Treatment: Implementing facial expression recognition systems in veterinary care helps in early detection of stress, pain, or emotional distress in animals. This assists veterinarians in providing timely and targeted care, leading to improved health outcomes for pets.

4. Education and Awareness: Research findings in this domain can be utilized in educational programs, helping individuals understand pet behaviors and emotions. It can raise awareness about the emotional lives of animals, promoting responsible pet ownership and ethical treatment.

5. Therapeutic and Interventional Applications: These advancements have potential therapeutic applications, particularly in animal-assisted therapy. Understanding and responding to pet emotions can aid in designing interventions to support individuals with

emotional or mental health challenges.

6. Technological Innovation: The research drives advancements in deep learning techniques applicable beyond pet facial recognition. It can inspire innovative solutions in computer vision, human-computer interaction, and emotional AI applications in diverse fields.

7. Psychological Understanding and Empathy: Insights gained from this research can contribute to understanding emotions beyond human interactions. It can advance the study of emotions, empathy, and social cognition, impacting psychology and behavioral sciences.

8. Public Engagement and Ethical Considerations: These studies encourage discussions on the ethical treatment of animals, fostering responsible societal attitudes toward animals' emotional experiences and well-being.

Overall, the societal impact of research in pet facial expression recognition using deep learning lies in enhancing relationships between humans and pets, improving animal welfare practices, fostering empathy, and advancing technological and scientific domains for the benefit of both animals and society as a whole.

5.2 Impact on the Environment

Research endeavors utilizing facial expression recognition through deep learning and tools like Google Colab present a nuanced environmental impact. Leveraging cloud-based platforms such as Google Colab potentially diminishes the necessity for personal high-end computational hardware, ostensibly reducing energy consumption and resource utilization associated with individual computing setups. These platforms often optimize energy use in data center operations, consolidating workloads for heightened efficiency, though the overall impact depends on the energy sources powering these data centers. While these platforms facilitate remote collaboration, mitigating the need for physical meetings and paper-based documentation, the energy-intensive nature of training large deep learning models, like EfficientNetB5, poses a consideration.

Consequently, while the utilization of cloud-based platforms can curtail individual hardware requirements and promote remote work practices, the environmental impact is contingent on various factors, including data center energy sources, model complexity, and resource utilization during model training. Balancing technological advancements with sustainable computing practices remains pivotal in minimizing the environmental footprint of such research endeavors.

5.3 Ethical Aspects

The research project can raise several ethical considerations that necessitate careful attention and responsible handling throughout the research process.

1. **Privacy and Consent:** Respecting the privacy and consent of pet owners is crucial when collecting and using pet facial expression data. Obtaining informed consent, where applicable, and ensuring data anonymization or pseudonymization to protect the identity of pets and owners is essential.

2. **Animal Welfare:** Prioritizing the well-being and ethical treatment of animals involved in data collection or experimentation is paramount. Ensuring that animals are not subjected to any harm, stress, or discomfort during image acquisition or data-gathering processes is essential.

3. **Bias and Fairness:** Mitigating biases in the dataset and the developed model is critical. Ensuring a diverse representation of different pet species, breeds, ages, and expressions within the dataset helps prevent biases that could lead to unfair treatment or misinterpretation of certain expressions.

4. **Transparency and Accountability:** Maintaining transparency in research methodologies, data handling, and model development processes is essential. Providing clear documentation about the dataset sources, labeling processes, and model performance metrics enhances accountability and trustworthiness.

5. Potential Misuse: Awareness of the potential for misuse of facial expression recognition technology is crucial. Preventing the technology from being exploited for purposes that may infringe on privacy rights, surveillance, or unethical treatment of animals is important.

6. **Social and Cultural Sensitivities:** Recognizing and respecting diverse cultural perceptions of pets and their expressions is crucial. Cultural differences in interpreting pet emotions should be considered to avoid misunderstanding or misinterpretation of expressions.

7. **Beneficence and Non-maleficence:** Ensuring that the research aims to benefit pets, their owners, or the field of veterinary science without causing harm or distress to the animals is a primary ethical consideration.

8. **Regulatory Compliance:** Adherence to ethical guidelines and regulatory frameworks governing animal research, data privacy, and animal welfare is essential. Compliance with institutional review boards and ethical committees ensures adherence to established ethical standards.

9. **Long-term Impact:** Consideration of the long-term implications of deploying facial expression recognition technology in various settings is crucial. Anticipating and addressing potential societal, ethical, and psychological impacts of widespread use is imperative.

In summary, ethical considerations in facial expression recognition research involving pets using deep learning encompass aspects of privacy, animal welfare, fairness, transparency, potential misuse, cultural sensitivities, regulatory compliance, and the long-term societal impact. Prioritizing ethical principles throughout the research process is essential to ensure responsible and morally sound practices in this field.

CHAPTER 6

SUMMARY, CONCLUSION, AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the study

The study focuses on the development of a robust framework for facial expression recognition in pets using deep learning methodologies, specifically exploring the application of EfficientNetB5 architecture. The methodology involves meticulous data collection, curation, and processing, emphasizing ethical considerations such as animal welfare, privacy, fairness, and transparency throughout the research process. Leveraging Google Colab, the research harnesses the computational capabilities of cloud-based platforms while addressing potential environmental impacts associated with deep learning model training. Ethical aspects surrounding data privacy, animal welfare, and potential societal implications of deploying facial expression recognition technology are carefully examined. The study not only aims to advance the understanding of pet emotions but also emphasizes responsible research practices and ethical considerations in the domain of animal-centric deep learning applications.

6.2 Conclusions

In conclusion, this study represents a significant step towards advancing the field of facial expression recognition in pets through the lens of deep learning. Leveraging methodologies centered on the EfficientNetB5 architecture and Google Colab, the research has strived to create a robust framework for accurately detecting and interpreting pet emotions. The emphasis on ethical considerations, including privacy, animal welfare, fairness, and transparency, underscores the commitment to responsible research practices. By navigating the complexities of data collection, processing, and model development, this study not only contributes to our understanding of pet emotions but also highlights the importance of ethical guidelines and environmental consciousness in technological advancements. Moving forward, the integration of deep learning into animal-

centric domains necessitates continued adherence to ethical principles, paving the way for responsible innovation benefiting both animals and human-animal interactions.

6.3 Implication for Future Study

Future studies in facial expression recognition for pets using deep learning could explore advanced model architectures beyond EfficientNetB5, delve into multi-species analysis considering variations in facial anatomy, conduct longitudinal studies tracking changes in pet emotions over time, develop comprehensive ethical frameworks, investigate real-time applications and human-animal interaction, mitigate biases, assess environmental impact, explore clinical applications in veterinary care, and extend research into human-computer interaction scenarios. These avenues offer promising directions for refining accuracy, ethical considerations, and practical applications of pet emotion recognition, building upon the foundational work laid by this study.

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