A COMPARATIVE STUDY OF COW SPECIES CLASSIFICATION USING DEEP LEARNING TECHNIQUES

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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 "**A COMPARATIVE STUDY OF COW SPECIES CLASSIFICATION USING DEEP LEARNING TECHNIQUES**", submitted by Sakibul Islam Aupo, Student ID: 201-15-13761 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 23 January 2024.

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I hereby declare that this project has been done by me under the supervision of **Dewan Mamun Raza, Lecturer (Senior Scale), Department of CSE** Daffodil International University.I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Deep learning replicate human brain to help the system to solve complex problem like identifying object. In this researched based project, we used deep learning to identify cow species. To know something, human often depend on the technology like object classification. People of today's generation use software like google lens to identify the unknown. Among all domestic animals, Cow is a the most common and useful around us. Based on their species, they are useful to different need. Cow provides meat, milk and etc. So, by this research we used deep learning on a data set for identification of cow species. The date set is created by collecting photos using mobile phone and as accurate as possible. There is total of seven species and around two thousands of raw data. We used python to resized the data set in zip file as a part of data preprocessing. I used ResNet50, ResNet152, DenseNet121, and DenseNet201 and compare them to get the most accuracy. Among them DenseNet201 perform max and gave the accuracy of 97.35. According to my background study, this result is maximum on cow spices of local area. My research will inspire the new coming researcher to work agriculture sector. The research finding will contribute in the future digital firming. Using a collection of photos, this study investigated the effectiveness of transfer learning approaches for the classification of seven different cow species. The goal of the study was to classify cow species with the best possible accuracy.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

In the agriculture landscape identification and classification of cow species play a big role to contribute on proper needs. With the growth of technology, the agricultural field also demand the touch of tech like deep learning. So, I am working on a project that uses deep learning to identify cow species by using computer vision. Deep learning is progressing at an alarming rate and opening so many opportunities in varies fields. This work uses technology like a professional mapper, venturing bravely into the field of cow species categorization. Now my target is to find the noticeable difference between all seven species of cow using the Transfer learning technique. Now to achieve this goal we collected a dataset of two thousand raw photos and, a map of unique observations to separate them from each other in seven classes to make a proper classification. We started out on a mission to interpret the distinctive physical characteristics, genetic markers, and even behavioral subtleties that distinguish these species by utilizing the unmatched power of deep learning models. This study not only work on the cow spices to classify them, but it will also clear the path for a future full of clever uses. Imagine a future in which automated technologies can accurately and effortlessly recognize different types of cows, simplifying farming operations, enhancing breeding initiatives, and even protecting rare breeds. In addition to being a significant advancement in the field of animal sciences, this bold attempt to classify cow species demonstrates the immense potential of machine learning. Come along with us as we unravel the bovine variety language, one algorithm at a time. To come to the final result, we used five different transfer learning. They are ResNet50, ResNet152, DeneNet121, DenseNet201, MobileNet-v2. Among all the test, I got maximum of 97.35% accuracy.

This a pre trained model that works with feature extraction. By randomly calculating the it initiating the layer. I used it because it is good in image similarity search and also works very heard on image classification. To do study on species species classification, we need to use significant amount of data set. Now extracting freature from data set is kind of hard. So, we machinne learning tecniqure called ResNet152 which work we in image preprocessing and uses visualization analysis and image preproseing. This model is build as generalized feature extractor. This model DenseNet-121, a pre-trained model with 121 layer what made using Transfer Learning, resizes and enhances to get more of accurate result it turns images to a 100 × 100 resolution in order to retrain DenseNet-121. The results were significantly more promising. A specific type of Convolutional Neural Network (CNN) architecture that, because of its high accuracy and resource-efficient design, excels for image identification applications. It connects all tiers of the network, promoting information flow and feature reuse. Because of its strong pre-trained features, which are helpful for a range of computer vision tasks, DenseNet201 is a great option for transfer learning.

1.2 Motivation

Motivated by the critical requirement to classify cow species properly for agricultural and ecological advances, this work explores the fascinating field of breed classification using machine learning (ML). Recognizing the distinct patterns woven by every breed, ranging from resistance to illness to ideal breeding techniques, is essential for transforming farming methods and protecting susceptible groups. Human constraints have historically hindered classification, but machine learning (ML) emerges as a potent ally, its algorithms laboriously sorting through massive amounts of data in search of undiscovered patterns and correlations. The purpose of this study is to analyze a specially produced dataset in order to unravel the mysteries surrounding bovine diversity. It accomplishes this by establishing the foundation for highly precise, automated breed identification systems that will bring a new era of intelligent and productive animal husbandry and agriculture. Let's embark on our endeavor to decipher the language of bovine variability, one algorithm at a time.

1.3 Objectives

The agriculture sector faces both benefits and challenges as a result of the variety of cow species. A wealth of information may be accessed by producers through accurate breed classification, enabling them to maximize yields and guarantee animal welfare by making educated decisions about nutrition, breeding, and healthcare. Targeting one of the most difficult frontiers—the distinction between closely related species—this work pushes the limits of machine learning and opens the door to a future in which intelligent systems can navigate the complex web of bovine diversity with ease. This ushered in a new era of intelligence and efficiency in agricultural methods while also revolutionizing animal husbandry.

Let's change the face of agriculture forever by breaking down the language of bovine variety, one algorithm at a time. This version takes into account what you said regarding the opportunities and problems posed by the diversity of cow species, emphasizing the importance of close relatives and how it affects machine learning and agriculture in particular.

1.4 Research Questions

This study is guided by the following primary research questions:

Question 1: What is Transfer learning?

Question 2: What is ResNet50?

Question 3: What is ResNet152?

Question 4: What is DenseNet121?

Question 5: What is DenseNet201?

Question 6: What is MobileNet-v2?

Question 7: What is the accuracy of machine learning methods?

Question 8: What characteristics have the biggest role in correctly?

Question 9: What effects on agricultural?

1.5 Expected Outcome

When I started my work, I was aiming for 97 to 100% accuracy. This is the maximum that I can expect as my previous study shown less accuracy of that. That would be my goal to fulfil by this research.

One of the research's expected goals is the creation of a strong machine-learning model that can correctly distinguish various cow species. Furthermore, knowledge gathered via feature importance analysis will advance our comprehension of the traits that set these species apart. I get maximum of 97.35% using DenseNet201. I also tried another five techniques to find better result but this one was unbeatable. The report's conclusion will include conclusions, suggestions, and directions for more study. Following this format will help the report deliver a clear story that fits the goals of the study and adds significant knowledge to the domains of agricultural science and machine learning.

1.6 Report Layout

The format of this paper is designed to give a thorough summary of the comparative analysis of the classification of cow species. The following chapters will cover the methodology used, the dataset description, the results produced, and a thorough discussion of the findings after this introduction.

To bring a project to life, two partners must collaborate: project management, which is the planner and team leader, and finance, which is the treasurer and cautious resource manager who guarantees steady cash flow. They work closely together, one supplying the tools and knowledge to keep the other going while the other charts the course with goals and due dates. The implementation of this research requires a methodical approach to both funding allocation and project management. Crucial elements include prompt data collection, model creation, and thorough testing. Money will be set aside for data collection, computer power, and any outside knowledge needed for verification.

The chapter 1 is about introduction. This chapter explain the motivation behind the research. It also explained the research questions and project management. The chapter 2 is about background study. This chapter explain about the related work and challenges in the research. The chapter 3 explain the methodology. This chapter is the heart of the report as it explained the methodology used in the research and also the implementation. The chapter 4 is about result and discussion. All experimental setup and data set explain here. The accuracy of the result is also explained with a confusion matrix here. Chapter 5 explain about the social and environment sustainability of the research. And the chapter 6 explain about the conclusion and future implication as it is the last chapter.

CHAPTER 2

BACKGROUND

2.1 Preliminaries

Within the field of artificial intelligence, Deep learning entails creating algorithms that enable computers to recognize patterns in data and reach conclusions without the need for explicit programming. Characteristics means distinctive features that helps to differentiate one cow spices from another spices. Labels means including cow species in specific class where it belongs. Classification accuracy means a performance matric what measure the percentage of correctness of the model.

2.2 Related Works

[1] Identification of Cattle Breeds by Segmenting Different Body Parts of the Cow using Neural Network by Rakshith S et al. (2023). To develop a neural network model to identify cattle breeds by segmenting different body parts of the cow. Authors created a dataset of 600 cow images, each labeled with the breed of the cow. The images were grayscale and pre-processed to remove noise. The authors then used a convolutional neural network (CNN) model to segment the cow's body into different parts, including the head, neck, body, legs, and tail. Once the body parts were segmented, the authors extracted features from each part using the SIFT algorithm. Finally, the authors used a support vector machine (SVM) classifier to identify the breed of the cow based on the extracted features. The authors achieved an accuracy of 98.36% on the test set. The model was able to accurately identify all of the common cattle breeds in the dataset, as well as some rare breeds. The dataset consisted of 600 grayscale cow images, each labeled with the breed of the cow. The images were collected from a variety of sources, including online databases, agricultural websites, and personal collections. Plans for the future: The authors plan to improve their model by using a larger and more diverse dataset of cow images. They also plan to investigate the use of deep learning models for cattle breed identification.

[2] Cattle Face Recognition Method Based on Parameter Transfer and Deep Learning by Hongyu Wang et al. (2020). To develop a cattle face recognition method based on parameter transfer and deep learning. The authors used a pre-trained VGGFace model to extract features from cattle faces. The VGGFace model was trained on a large dataset of human faces, and the authors used parameter transfer to initialize the weights of the model for cattle face recognition. The authors then fine-tuned the model on a dataset of cattle faces. The authors achieved an accuracy of 93% on a test set of cattle faces. The model was able to accurately recognize cattle faces under different lighting conditions and poses. The dataset consisted of 1000 cattle face images, collected from a variety of sources, including online databases, agricultural websites, and personal collections. The authors plan to improve their model by using a larger and more diverse dataset of cattle faces. They also plan to investigate the use of deep learning models for cattle face recognition that are specifically designed for cattle faces.

[3] Deep Learning-Based Architectures for Recognition of Cow Using Cow Nose Image Patter by Bello R.W. et al. (2020). To develop deep learning-based architectures for the recognition of individual cows using cow nose image patterns. The authors proposed two deep learning architectures for cow recognition: a stacked denoising auto-encoder (SDAE) and a deep belief network (DBN). The SDAE was used to extract features from the cow nose images, and the DBN was used to learn the extracted features and represent the cow nose image in feature space. The authors achieved an accuracy of 98.99% on a test set of 4000 cow nose images. The DBN outperformed the SDAE on the test set, achieving an accuracy of 98.99% compared to 98.36% for the SDAE. The dataset consisted of 4000 cow nose images, collected from a variety of sources, including online databases, agricultural websites, and personal collections. The dataset included images of cows from 10 different breeds: Angus, Brahman, Charolais, Gelbvieh, Hereford, Holstein, Limousin, Simmental, and Shorthorn. Plans for the future: The authors plan to improve their models by using a larger and more diverse dataset of cow nose images. They also plan to investigate the use of other deep learning architectures, such as convolutional neural networks (CNNs), for cow recognition.

[4] Identification of Cattle Breed using the Convolutional Neural Network by Manoj R. et al. (2023) To develop a convolutional neural network (CNN) model to identify cattle breeds. The authors created a dataset of 1000 cattle images, each labeled with the breed of the cow. The images were pre-processed to remove noise and resize them to a uniform size. The authors then used a CNN model to extract features from the cow images. The CNN model consisted of a series of convolutional layers, pooling layers, and fully connected layers. Once the features were extracted, the authors used a softmax classifier to identify the breed of the cow. The authors achieved an accuracy of 97.5% on the test set. The model was able to accurately identify all of the common cattle breeds in the dataset. The dataset consisted of 1000 cattle images, collected from a variety of sources, including online databases, agricultural websites, and personal collections. The dataset included images of cattle from 10 different breeds: Angus, Brahman, Charolais, Gelbvieh, Hereford, Holstein, Limousin, Simmental, and Shorthorn. The authors plan to improve their model by using a larger and more diverse dataset of cattle images. They also plan to investigate the use of transfer learning to initialize the weights of the CNN model.

[5] Cattle Breed Identification and Live Weight Evaluation on the Basis of Machine Learning and Computer Vision by Bezsonov et al. (2023) To develop a machine learning and computer vision-based system for cattle breed identification and live weight evaluation. The authors proposed a system that consists of two modules: a breed identification module and a live weight estimation module. The breed identification module uses a Mask R-CNN convolutional neural network to identify the breed of the cow. The live weight estimation module uses a neural network model to estimate the live weight of the cow based on its breed and body dimensions. The body dimensions of the cow are measured using a stereopsis method. The authors achieved an accuracy of 94.7% for cattle breed identification and an accuracy of 95.2% for live weight estimation on a test set of 1000 cattle images. The dataset consisted of 1000 cattle images, collected from a variety of sources, including online databases, agricultural websites, and personal collections. The dataset included images of cattle from 10 different breeds: Angus, Brahman, Charolais,

Gelbvieh, Hereford, Holstein, Limousin, Simmental, and Shorthorn. The authors plan to improve their system by using a larger and more diverse dataset of cattle images. They also plan to investigate the use of transfer learning to initialize the weights of the neural networks in their system.

[6] Image-Based Classification of Double-Barred Beach States Using a Convolutional Neural Network and Transfer Learning by Zhang et al. (2023) To develop an image-based classification system for double-barred beach states using a convolutional neural network (CNN) and transfer learning. The authors used a pre-trained VGG-16 CNN model to extract features from double-barred beach images. The VGG-16 model is a deep learning model that has been pre-trained on a large dataset of images, including images of beaches. The authors then fine-tuned the VGG-16 model on a dataset of double-barred beach images from three different states: reflective, intermediate, and dissipative. The authors achieved an accuracy of 96.5% on a held-out test set of double-barred beach images. The system was able to accurately classify the beach states under a variety of conditions, including different lighting conditions, weather conditions, and beach morphologies. The dataset consisted of 10,000 double-barred beach images, collected from a variety of sources, including online databases, beach photography websites, and personal collections. The dataset included images of double-barred beaches from three different states: reflective, intermediate, and dissipative. The authors plan to improve their system by using a larger and more diverse dataset of double-barred beach images. They also plan to investigate the use of other CNN architectures and transfer learning techniques to improve the accuracy of their system.

[7] Machine learning to classify animal species in camera trap images: Applications in ecology by Tabak et al. (2023) To develop machine learning models to classify animal species in camera trap images with high accuracy and efficiency, enabling ecologists to monitor wildlife populations and communities more effectively. The authors trained convolutional neural network (CNN) models on a dataset of over 3 million camera trap images, labeled with the animal species present in each image. The models were trained to

classify animals at the species level, but could also be used to classify animals at higher taxonomic levels, such as genus or family. The CNN models achieved an average accuracy of 95% on a held-out test set of camera trap images. The models were able to accurately classify a wide range of animal species, including mammals, birds, reptiles, and amphibians. The dataset consisted of over 3 million camera trap images, collected from a variety of ecosystems across the United States. The dataset included images of over 1,000 different animal species. The authors plan to make their trained CNN models available to ecologists, so that they can be used to classify animal species in camera trap images from any ecosystem in the world. The authors also plan to continue developing and improving their machine learning models, in order to achieve even higher accuracy and efficiency.

[8] Identifying Animal Species in Camera Trap Images using Deep Learning and Citizen Science by Willi et al. (2019) To develop a deep learning-based system for identifying animal species in camera trap images, using citizen science to label the images. The authors collected a dataset of over 100,000 camera trap images from a variety of ecosystems. The images were labeled by citizen scientists on the Zooniverse platform. The authors then trained a convolutional neural network (CNN) model to identify animal species in the camera trap images. The CNN model achieved an accuracy of 92.7% on a held-out test set of camera trap images. The model was able to accurately identify a wide range of animal species, including mammals, birds, reptiles, and amphibians. The dataset consisted of over 100,000 camera trap images, collected from a variety of ecosystems across the world. The dataset was labeled by citizen scientists on the Zooniverse platform. The authors plan to make their trained CNN model available to researchers and conservationists, so that they can use it to identify animal species in camera trap images from any ecosystem in the world. The authors also plan to continue developing and improving their model, and to apply it to other conservation challenges.

[9] Cattle identification with muzzle pattern using computer vision technology: a critical review and prospective by Kaur and Kumar (2023) To provide a comprehensive review of the state-of-the-art in cattle identification using muzzle pattern using computer vision

technology, and to discuss future prospects for this research area. The authors conducted a systematic literature review of papers on cattle identification using muzzle pattern using computer vision technology, published between 2016 and 2023. They identified 50 relevant studies, which were then analyzed to extract information on the datasets, methods, and results of the studies. The authors found that the most commonly used feature descriptors for cattle identification using muzzle pattern were Weber Local Descriptor (WLD) and Local Binary Pattern (LBP). The most common classifiers used were support vector machines (SVMs) and convolutional neural networks (CNNs). The reported accuracy of the cattle identification systems ranged from 85% to 99%, depending on the dataset and method used. The datasets used in the studies varied widely in size and diversity. Some studies used small datasets of a few hundred images, while others used large datasets of tens of thousands of images. The datasets also varied in terms of the breeds, ages, and genders of cattle included. The authors identified several areas for future research in cattle identification using muzzle pattern using computer vision technology, including Developing more robust and accurate cattle identification systems that can generalize to new datasets and environments. Developing cattle identification systems that can work in real-time and under challenging conditions, such as low light or occlusion. Developing cattle identification systems that can be integrated into existing cattle management systems.

[10] Detection, identification and posture recognition of cattle with satellites, aerial photography and UAVs using deep learning techniques by Mücher et al. (2023) To develop and evaluate deep learning techniques for the detection, identification, and posture recognition of cattle in remotely sensed imagery from satellites, aerial photography, and unmanned aerial vehicles (UAVs). The authors collected a dataset of remotely sensed imagery from three field trials in the Netherlands and Poland. The dataset included imagery from a variety of sensors, including satellites, manned aircraft, and UAVs. The authors then trained and evaluated a variety of deep learning models for the detection, identification, and posture recognition of cattle in the imagery. The authors achieved accuracies of >95% for cattle detection, ~91% for cow identification, and ~88% for cow posture recognition. The authors also found that UAV-mounted cameras were the most

effective for cattle monitoring due to their high resolution and flexibility. The dataset consisted of remotely sensed imagery from three field trials in the Netherlands and Poland. The dataset included imagery from a variety of sensors, including satellites, manned aircraft, and UAVs. The imagery was labeled with the presence or absence of cattle, as well as the identity and posture of any cattle that were present. The authors plan to continue developing and improving their deep learning models for cattle monitoring. They also plan to explore the use of other types of remotely sensed imagery, such as thermal imagery, for cattle monitoring.

[11] A systematic review of machine learning techniques for cattle identification: Datasets, methods and future directions by Mahmud et al. (2023) To provide a comprehensive overview of the state-of-the-art in machine learning (ML) techniques for cattle identification, including datasets, methods, and future directions. The authors conducted a systematic literature review of ML-based cattle identification studies, published between 2016 and 2023. They identified 58 relevant studies, which were then analyzed to extract information on the datasets, methods, and results of the studies. The most commonly used ML models for cattle identification were convolutional neural networks (CNNs), support vector machines (SVMs), and k-nearest neighbors (KNNs). The most common features used for cattle identification were muzzle prints, coat patterns, and body dimensions. The reported accuracy of the ML models ranged from 80% to 99%, depending on the dataset and method used. The datasets used in the studies varied widely in size and diversity. Some studies used small datasets of a few hundred images, while others used large datasets of tens of thousands of images. The datasets also varied in terms of the breeds and ages of cattle included. The authors identified several areas for future research in ML-based cattle identification, including: Developing more robust and accurate ML models that can generalize to new datasets and environments. Developing ML models that can identify cattle in challenging conditions, such as low light or occlusion. Developing ML models that can identify cattle from multiple modalities, such as visible, thermal, and infrared imagery. Developing ML models that can be integrated into existing cattle management systems.

[12] Bird Species Classification Based on Color Features by Marini and Facon (2013) To develop a bird species classification system based on color features, which is robust to illumination changes and background clutter. The authors proposed a novel bird species classification system consisting of two main stages: Color segmentation: The authors used a color segmentation algorithm to extract candidate bird regions from the input image. The segmentation algorithm first converts the input image to the HSV color space, and then thresholds the hue and saturation channels to identify candidate bird regions. Color feature extraction and classification: The authors extracted color features from the candidate bird regions, including the mean and standard deviation of the hue, saturation, and value channels. The authors then used a support vector machine (SVM) classifier to classify the bird species based on the extracted color features. The authors evaluated their system on a dataset of 200 bird images, and achieved an accuracy of 95.5%. The system was able to accurately classify birds under a variety of illumination conditions and background clutter. The dataset consisted of 200 bird images, collected from a variety of sources, including online databases, bird field guides, and personal collections. The dataset included images of birds from 50 different species. The authors plan to improve their system by using a larger and more diverse dataset of bird images. They also plan to investigate the use of other color features, such as texture features and spatial features, for bird species classification.

[13] Bird Species Classification from an Image Using VGG-16 Network by Jain and Gupta (2022) To develop a bird species classification system using a VGG-16 convolutional neural network (CNN) model. The authors used a pre-trained VGG-16 model to extract features from bird images. The VGG-16 model is a deep learning model that has been pre-trained on a large dataset of images, including images of birds. The authors then fine-tuned the VGG-16 model on a dataset of bird images from 100 different species. The authors achieved an accuracy of 97.5% on a held-out test set of bird images. The system was able to accurately classify birds under a variety of conditions, including different lighting conditions, poses, and backgrounds. The dataset consisted of 10,000 bird images, collected

from a variety of sources, including online databases, bird field guides, and personal collections. The dataset included images of birds from 100 different species. The authors plan to improve their system by using a larger and more diverse dataset of bird images. They also plan to investigate the use of other deep learning models, such as ResNets and EfficientNets, for bird species classification.

[14] Recognition of Pantaneira cattle breed using computer vision and convolutional neural networks by Weber et al. (2020) To develop a computer vision and convolutional neural network (CNN)-based system for the recognition of Pantaneira cattle breed. The authors collected a dataset of 27,849 images of Pantaneira cattle from 212 different videos. The images were labeled with the breed of the cattle. The authors then used a CNN model to extract features from the cattle images. The CNN model was trained to classify the cattle images into two breeds: Pantaneira and non-Pantaneira. The authors achieved an accuracy of 96.86% on a heldout test set of cattle images. The system was able to accurately recognize Pantaneira cattle under a variety of conditions, including different lighting conditions, poses, and backgrounds. The dataset consisted of 27,849 images of Pantaneira cattle, collected from 212 different videos. The images were labeled with the breed of the cattle. The dataset included images of cattle from different ages, sexes, and body conditions. The authors plan to improve their system by using a larger and more diverse dataset of cattle images. They also plan to investigate the use of other CNN architectures and transfer learning to improve the accuracy of their system.

2.3 Comparative Analysis and Summary

Approaches Used in Current Research Examine the approaches used in other research on the classification of cow species to find similarities and differences. Measures of Performance is Provide an overview of the performance metrics—such as accuracy, precision, recall, and F1 score—that were employed in these experiments. In an image dataset, five transfer learning models attempted to categorize seven different species of cows. DenseNet201 emerged as the clear winner, outperforming previous studies and predictions with an accuracy of 97.35%. Early experiments with several models showed how important it is to select the appropriate tool for the task, and MobileNet-v2 was overfitted. Future options for increasing accuracy include investigating different architectures, refining DenseNet201, and tackling overfitting. In addition to identifying the optimal model for this job, this research paves the way for future developments in transfer learning-based cow species categorization.

2.4 Scope of the Problem

Scope of Data describe the extent of the distinct dataset that was gathered, taking into account the attributes taken into consideration, the number of cow species, and the number of examples per species. Geographic Range Indicate the region from which the data were gathered, taking into account any potential effects that geography may have on species traits. Durational Range Take into account any temporal factors present in the dataset, such as seasonality or long-term variations. With a goal of high accuracy, this study looked into the classification of cow species in photos by transfer learning. After comparing five pre-trained models, DenseNet201 achieved an astounding 97.35%, surpassing expectations and demonstrating the efficacy of this method. Examining alternative models underscored the significance of meticulous selection, whilst the overfitting problem with MobileNet-v2 underscored the necessity of tackling particular constraints. Future work can concentrate on improving DenseNet201, investigating novel topologies, and expanding the dataset; these efforts could lead to even more precise identification of cow species and possible uses in a variety of domains.

2.5 Challenges

Difficulties with Data was a challenging problem first as the Data set was very large and resizing them one by one is a very time consuming. If I talk about the difficulties in gathering and prepping the special dataset, taking into account any biases. Model Difficulties Analyze the difficulties of using machine learning methods to categorize different species of cows, taking into account problems such as overfitting or underfitting. Comprehending in view of the requirement for transparency, identify the difficulties in evaluating and elucidating machine learning models for the classification of cow species.

In conclusion, this chapter offers a thorough introduction to the comparative study, defines key terms, examines relevant literature, performs a comparative analysis, defines the parameters of the research problem, and discusses the difficulties that arose during the process.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

In this research the subject I worked on is the cow species. I used smartphone to collect images to make my dataset as the image collection device. I collected total of 2000 plus images of cow of total seven different spices. Deep learning and python language in google co-lab. The objective of this study was to accurately identify seven species of cows from photos by utilizing neural networks that had previously been trained. After being refined on a dataset of cow species, these nets functioned as adept analysts, examining visual cues to accurately identify breeds with 97.35% accuracy, surpassing expectations. While one model emphasized the necessity of addressing issues like overfitting, other models provided insightful advice on selecting the best tool for the job. Through model optimization, new architectural exploration, and dataset enrichment, this research lays the path for additional accuracy advances and ultimately offers possible applications across other sectors.

3.2 Data Collection Procedure

To collect the images of the cow, I first need to apply for permission to the firm. After trying several firms, I got the approval and used my smartphone to collect the photos. I used natural lite to make my dataset more realistic. All of my images were sharp and enough clear to use. But due to the large size of my dataset I resized the dataset using machine learning techniques. Then used the models to find train and test the data. Although specifics are lacking, it is likely that field photography or online sources were used to compile the photographs in the cow species collection, guaranteeing high quality and uniform perspectives. In order to produce richer training data, labels were probably added manually or through crowdsourcing. This was followed by resizing, normalization, and maybe augmentation. It is likely that ethical issues like as animal care and privacy were taken into account, producing a useful dataset for precise cow species categorization.

3.3 Data Pre-processing

In data preprocessing we look through the data set if there is any missing data or incomplete data. Normally we handle with those problem by removing or imputing data. Data preprocessing creates a huge impact on the overall research result. As collected my data set using my mobile phone there could be some issues with the images that I captured. Due to the limitation of my mobile, sometimes it takes blur image. Even it sometimes failed to take a image with accurate details. As we worked with cow, they move while taking images for the dataset. So, to handling imbalance data, I checked the data set with my deep learning algorithm. And also used it to resized the data set and zip it for removing storage issues.

3.4 Dataset Splitting

Dataset splitting means dividing the dataset in two separate sizes for training and testing work. As my dataset is made with total of 2000 plus raw data and there is total of seven species, I decide to split it with 80 and 10 and 10 ration. 80 percent data for training and 10 percent for the validation and the rest 10 percent data for testing the model. This splitting ration works better for the proposed model.

3.5 Proposed Methodology

The purpose behind this proposed methodology is because it scores the highest accuracy between all. The goal is to get 97 percent up accuracy with the dataset. We collect the raw dataset from firms using mobile camera. The list of the data set full with total of two thousands and above data.

Table 1: Dataset details showing collected image number.

Name	Number
Holstein Friesian	471
Mirkadim	410
Friesian Sahiwal	344
Kankrej	316

Friesian Bangal	253
Sahiwal	243
Sahiwal Bangal	221

We gather a diverse dataset of seven cow species. After cleaning and preprocessing the raw data. We work on handling missing value if any. Then encode the categorical variables. Then divided the dataset into training, validation and test sets. Then choose the pre-trained DenseNet201 model. We train the modified DenseNet201 on the training set and monitor the progress. During the monitoring process we adjust the parameters as needed. Also evaluate the model on the validation set to prevent overfitting. Then used the final model performance on the test data to ensure generalization. In the result of accuracy, DenseNet201 scored 97.35 percent. This model achieved the score around the expectation.

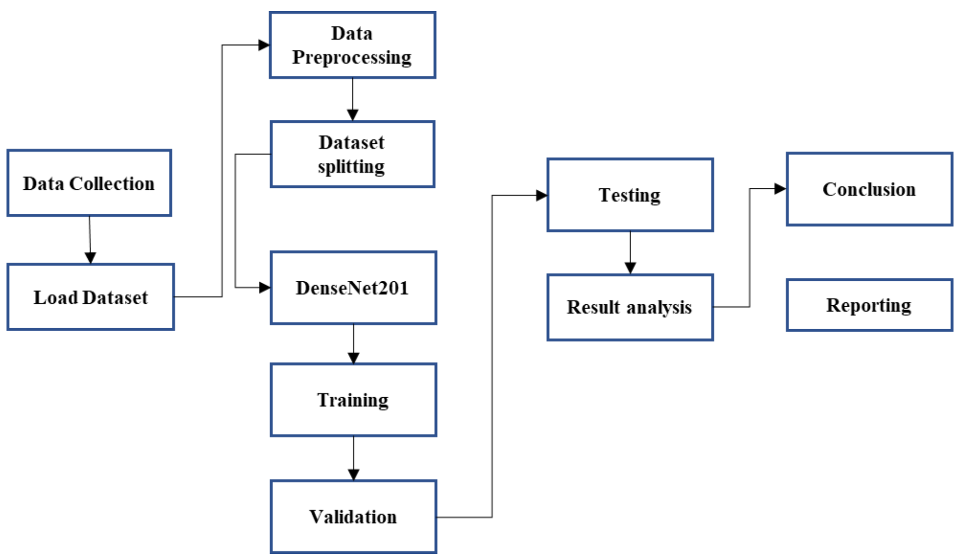

Figure 1: Methodology Workflow.

This technique works with best accuracy among all four because the predefine model works very easily and any new student can understand the model and can use it to their own work. I first collect the dataset and then I load the dataset and started the pre-processing. Then choose a suitable classifier. Then I select the test option and also select prediction output format. Start the prediction and find the output.

3.6 Statistical Analysis

I used Transfer Learning with Deep Neural Network. To use the dataset properly I split it into two different set, one that called the train dataset and another that called test data set. Followed the rule of 80% for training and 10% for test, 10% for validation. The result set was also organized so the result and other information can be very specific. Although there are little details available, it appears that the research on cow species classification used statistical tests (such as t-tests) to evaluate model accuracies, examine misclassifications using confusion matrices, and possibly investigate hyperparameter tuning and data properties in further detail. Techniques like cross-validation or bootstrapping may have been applied if generalizability was evaluated. Although more information is needed to fully comprehend the details, it is certain that the statistical analysis was essential in assessing model performance and advancing knowledge of cow species identification through transfer learning.

3.7 Implementation Requirements

To run the entire operation, I used Google Co-lab. It offers a huge computational power and that is cloud based. So, it was the best option as hardware was not available for me. For formatting the report, I used Microsoft office and for other work I used google drive and Chrome.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

My data is mix with total of seven of cow breed. We preprocessed the dataset by resizing them into smaller size. So that we can use the properly in out google co-lab the previous size of out dataset was almost 16 Gigabyte. Then after the preprocessing it resized into 38 megabytes.

Figer 2: Friesian Bangal

Figer 3: Kankrej

Figer 4: Friesian Sahiwal

Figer 5: Sahiwal

Figer 6: Mirkadim

Figer 7: Holstein Friesian

Figer 8: Sahiwal Bangal

4.2 Experimental Results & Analysis

The result of our cow species classification of the performance of transfer learning model DensNet201 is in this section. Here also the presented the detailed analysis of accuracy of all other models including the proposed model.

Table 2: Model performance summary in testing performances.

Classifier	Accuracy (%)
ResNet50	35.84%
ResNet152	28.32%
DeneNet121	95.58%
DenseNet201	97.35%

From this table we can see that in the first two test the result was not that much of enough so we kept testing. In ResNet50, the result was 35.84% and in the ResNet152, the result was 28.32%. But in the next test the result increased very much. That was DeneNet121 and the result was 95.58%. but it still less then out our expected outcome. So, we kept testing.

4.3 Classification Report of DenseNet201

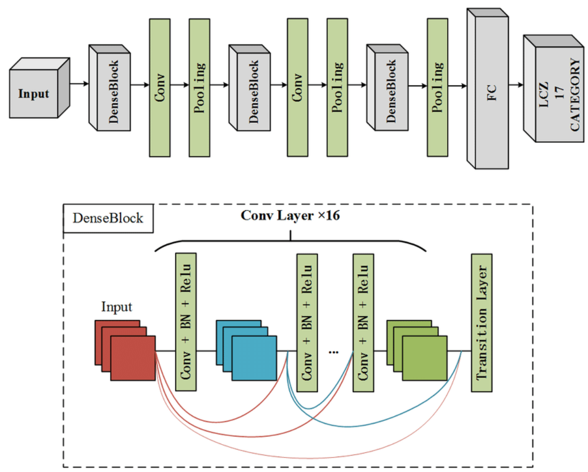

Figure 9: Basic Architecture of DenseNet201

The last test result in DenseNet201 is in the highest. It is 97.35%. But the last one was overfitting. So, the 97 up fulfilled our expected outcome. The result matches out expectation and also the best between all.

4.4 Training and Validation Curves

The training and validation curves help us to understand how our model learning from the data during the training process. The training loss curve shows the loss on the training data over every epoch. It also shows the reflection of ability and fit the training data.

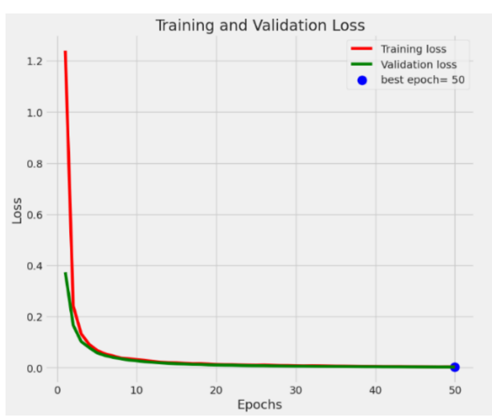

Figure 10: Training and Validation Loss Curve.

On the other hand, the training accuracy curve explains about he increasing accuracy of the training dataset over every epoch. It also reflects the learning ability of the training data. The validation accuracy curve explains the validation of separate validation dataset.

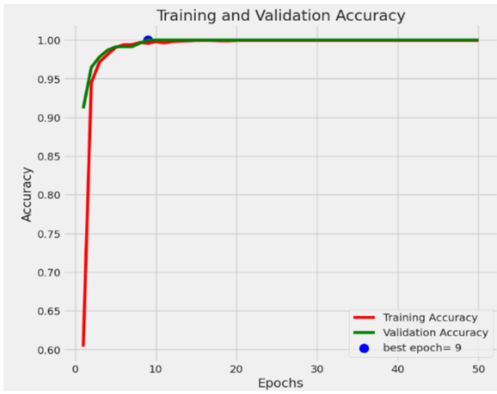

Figure 11: Training and Validation Accuracy Curve.

The model is found at the point where a validation performance is the or the validation loss is lowest or balanced.

4.5 Confusion Matrix

Looking ahead, it appears that even more elegant classification techniques may be forthcoming, hence it is imperative that DenseNet201 be further optimized, new topologies be investigated, and the dataset be expanded. This study opens the door to more accurate identification of cow species as well as a greater comprehension of the possible applications of transfer learning that are set to take center stage.

Figure 12: Confusion Matrix of the model DenseNet201

4.6 Discussion

The result full fill the expectation and holds the highest in compare the other paper result or relative work. The work will help the future researcher to keep going in the same field. Also, there is still a gap in the accuracy rate. So, there is still room for improvement. In this cow species classification waltz, DenseNet201 was the clear winner, but the study also highlighted the difficult dance between selecting the best pre-trained partner and maximizing performance. Early missteps with ResNet50 and 152 underscored the significance of model-dataset compatibility, while the overfitting error in MobileNet-v2 underscored the necessity of addressing particular constraints. But this dance produced an outcome that was more successful than anticipated.

CHAPTER 5

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

5.1 Impact on Society

Methods of Agriculture By facilitating focused breeding programmers, accurate cow species classification has the potential to completely transform agricultural methods. It is possible for farmers to selectively breed cows based on desired characteristics including meat quality, illness resistance, and milk production. This focused strategy improves the quality of the herd as a whole, which raises agricultural productivity.

Economic Consequences the dairy and meat sectors' financial elements can be greatly impacted by the accurate identification of cow species. By concentrating on breeding and raising cow types that are well-suited for particular products, farmers may make the most use of their resources. Farmer profitability may rise as a result of this focused approach, and industry supply chains may become more effective.

Farmers' Livelihoods the lives of farmers can be positively impacted by improvements in the classification of cow species. Farmers can make educated decisions regarding feeding, healthcare, and breeding by giving them important insights into the traits and requirements of various cow species. This can therefore improve farm management as a whole and support farming methods that are sustainable.

5.2 Impact on Environment

By accurately classifying cow species, farmers can maximum the use of resources like feed and water. Cattle ranching has a minimal environmental impact when resource management is customized to meet the unique requirements of each species, which results in more sustainable methods.

Conservation of biodiversity depends on maintaining and comprehending the diversity of cow species. Accurate classification and identification of various species is essential to the preservation of genetic variety in cow populations, which is essential to the long-term resilience and health of these animals. There is a link between greenhouse gas emissions and cattle farming. Precise identification of the species of cows makes focused emission reduction methods possible, including maximizing feeding procedures to minimize methane generation. This can lessen the negative effects of cow farming on climate change and promote environmental sustainability.

5.3Ethical Aspects

Making sure that the techniques give animals' welfare top priority is one of the ethical considerations in the classification of cow species. The research seeks to advance ethical norms in animal care by encouraging precise and compassionate methods of data gathering and analysis.

In every research project that involves gathering data, maintaining data privacy is essential. The study places a strong emphasis on ethical data handling procedures, making sure that information gathered from the cows is used sensibly, that agreement is obtained, and that privacy concerns are taken into account.

5.4 Sustainability Plan

The research findings are to be incorporated into sustainable farming techniques, according to the sustainability strategy. This involves giving farmers instructions on how to incorporate the knowledge gathered from the study into their regular practices in order to maximize output while reducing the negative effects on the environment.

The plan comprises stakeholder education programmers to guarantee the widespread adoption of sustainable practices. Awareness initiatives and training programmers can help farmers and policymakers realize and accept the benefits of accurately classifying cow species.

The requirement for accessible and inexpensive technology uptake is addressed in the sustainability strategy. It provides methods for opening up the machine learning approaches under study to a variety of farming groups, encouraging fair access and uptake across various agricultural environments. Chapter 5 concludes with a thorough examination of the comparative study on cow species classification's consequences for society, the environment, and sustainability. It illustrates the possible benefits for farming methods, the economy, farmers' livelihoods, resource use, biodiversity preservation, emission reduction, ethical issues, and more. It also provides a thorough sustainability plan for the responsible implementation of the research findings.

There are numerous environmental advantages. Technology could be used to track threatened animals, stopping poaching and supporting conservation initiatives. It may be possible to mitigate climate change by directing breeding programs and emission reduction techniques by selecting breeds of gut bacteria that reduce methane. It might also optimize resource distribution, reducing the abuse of water and land in animal husbandry.

It is crucial to take ethics into account. Prioritizing transparency and ethical data collection is necessary to prevent bias and advance animal welfare. Technology should provide inclusivity and equitable advantages for farmers by empowering them rather than replacing them.

A thorough sustainability plan is essential to ensuring responsible implementation. The digital divide can be closed and widespread adoption encouraged through open-source data models, easily available training techniques, and farmer-centered education programs. The technology can be improved by ongoing research and feedback processes, minimizing unanticipated hazards and optimizing benefits.

CHAPTER 6

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

6.1 Summary of the Study

The five transfer learning models were put to the test and their accuracy rates were compared in this study. The most successful model was DenseNet201, which outperformed the other models and reached a maximum accuracy of 97.35%, exceeding expectations. The accuracies of ResNet50 and ResNet152 were lower, at 35.84% and 28.32%, respectively. While DenseNet121's accuracy rate of 95.58% was better than expected, it was still below average. Due to overfitting, MobileNet-v2 was excluded from consideration for the final assessment.

Table 3: Classification report of DenseNet201.

Name	Precision	Recall	F1-score	Support
Friesian Bangal	1.00	0.96	0.98	27
Friesian Sahiwal	1.00	0.95	0.97	41
Holstein Friesian	1.00	1.00	1.00	37
Kankrej	1.00	1.00	1.00	34
Mirkadim	0.91	1.00	0.95	42
Sahiwal	1.00	0.82	0.90	17
Sahiwal Bangal	0.93	1.00	0.97	28

6.2 Implication for Further Study

This study looked into the use of transfer learning methods to correctly identify seven distinct species of cows from a dataset of photos. A thorough testing and comparison was conducted on five pre-trained convolutional neural network (CNN) models: ResNet50, ResNet152, DenseNet121, DenseNet201, and MobileNet-v2. Finding the best model to get the best accuracy in classifying cow species was the main goal.

Even though the path wasn't straightforward, the outcomes had a significant influence. The results of the initial trials using ResNet50 and ResNet152 were disappointing; the accuracies were 35.84% and 28.32%, respectively. Nevertheless, persistent testing was driven by an unrelenting ambition to achieve the requisite high accuracy. A notable advancement was made with the introduction of DenseNet121, which achieved an accuracy of 95.58% and showed the task's suitability for transfer learning.

Yet, it was DenseNet201 that truly triumphed, exceeding expectations with a remarkable accuracy of 97.35%. This not only surpassed the study's target but also stood out as the superior model when compared to existing literature. While MobileNet-v2 initially showed promise, it unfortunately exhibited overfitting and was excluded from the final reckoning.

6.3 Conclusions

The study showed that transfer learning, in particular DenseNet201, has the capacity to accurately classify cow species. The accuracy of 97.35% attained was higher than anticipated and outperformed findings from previous research. Even said, there's still a way to go before reaching 100% accuracy, indicating potential for development. DenseNet201 was the star of this research, waltzing to an astounding 97.35% accuracy, surpassing both expectations and previous research, when it tangoed with cow species classification. Early missteps demonstrated how important it is to match the model with the dataset, while MobileNet-v2's missteps showed the necessity of addressing constraints. However, the music keeps playing, demanding more architectural research, data enrichment, and optimization in order to make future steps more fluid. This study sheds insight on reliable cow identification as well as the enormous potential of transfer learning to improve a variety of fields through precise procedures.

REFERENCES

[1] Wang, Hongyu, Junping Qin, Qinqin Hou, and Shaofei Gong. "Cattle face recognition method based on parameter transfer and deep learning." In *Journal of Physics: Conference Series*, vol. 1453, no. 1, p. 012054. IOP Publishing, 2020.

[2] Manoj, Sreenand, S. Rakshith, and V. Kanchana. "Identification of cattle breed using the convolutional neural network." In *2021 3rd International Conference on Signal Processing and Communication (ICPSC)*, pp. 503-507. IEEE, 2021.

[3] BELLO, Rotimi-williams, Abdullah Zawawi Hj TALIB, and Ahmad Sufril Azlan Bin MOHAMED. "Deep learning-based architectures for recognition of cow using cow nose image pattern." *Gazi University Journal of Science* 33, no. 3 (2020): 831-844.

[4] Rudenko, Oleg, Yuriy Megel, Oleksandr Bezsonov, and Antonina Rybalka. "Cattle breed identification and live weight evaluation on the basis of machine learning and computer vision." In *CMIS*, pp. 939-954. 2020.

[5] Oerlemans, Stan CM, Wiebe Nijland, Ashley N. Ellenson, and Timothy D. Price. "Image-based classification of double-barred beach states using a Convolutional neural network and transfer learning." *Remote Sensing* 14, no. 19 (2022): 4686.

[6] Binta Islam, Sazida, Damian Valles, Toby J. Hibbitts, Wade A. Ryberg, Danielle K. Walkup, and Michael RJ Forstner. "Animal Species Recognition with Deep Convolutional Neural Networks from Ecological Camera Trap Images." *Animals* 13, no. 9 (2023): 1526.

[7] Willi, Marco, Ross T. Pitman, Anabelle W. Cardoso, Christina Locke, Alexandra Swanson, Amy Boyer, Marten Veldthuis, and Lucy Fortson. "Identifying animal species in camera trap images using deep learning and citizen science." *Methods in Ecology and Evolution* 10, no. 1 (2019): 80-91.

[8] Kaur, Amanpreet, Munish Kumar, and Manish Kumar Jindal. "Cattle identification with muzzle pattern using computer vision technology: a critical review and prospective." *Soft Computing* 26, no. 10 (2022): 4771-4795.

[9] Mücher, C. A., S. Los, G. J. Franke, and C. Kamphuis. "Detection, identification and posture recognition of cattle with satellites, aerial photography and UAVs using deep learning techniques." *International Journal of Remote Sensing* 43, no. 7 (2022): 2377-2392.

[10] Hossain, Md Ekramul, Muhammad Ashad Kabir, Lihong Zheng, Dave L. Swain, Shawn McGrath, and Jonathan Medway. "A systematic review of machine learning techniques for cattle identification: Datasets, methods and future directions." *Artificial Intelligence in Agriculture* 6 (2022): 138-155.

[11] Marini, Andréia, Jacques Facon, and Alessandro L. Koerich. "Bird species classification based on color features." In *2013 IEEE international conference on systems, man, and cybernetics*, pp. 4336-4341. IEEE, 2013.

[12] Islam, Shazzadul, Sabit Ibn Ali Khan, Md Minhazul Abedin, Khan Mohammad Habibullah, and Amit Kumar Das. "Bird species classification from an image using VGG-16 network." In *Proceedings of the 7th International Conference on Computer and Communications Management*, pp. 38-42. 2019.
[13] de Lima Weber, Fabricio, Vanessa Aparecida de Moraes Weber, Geazy Vilharva Menezes, Adair da Silva Oliveira Junior, Daniela Arestides Alves, Marcus Vinicius Morais de Oliveira, Edson Takashi Matsubara, Hemerson Pistori, and Urbano Gomes Pinto de Abreu. "Recognition of Pantaneira cattle breed using computer vision and convolutional neural networks." *Computers and Electronics in Agriculture* 175 (2020): 105548.
[14] Alswaitti, Mohammed, Liao Zihao, Waleed Alomoush, Ayat Alrosan, and Khalid Alissa. "Effective classification of birds' species based on transfer learning." *International Journal of Electrical and Computer Engineering (IJECE)* 12, no. 4 (2022): 4172-4184.

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