Image Based Cattle Nose Print Recognition Technology: A Game Changer for Individual Cow Identification and Insurance Integrity in Bangladesh's Livestock Industry

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FINAL YEAR DESIGN PROJECT REPORT

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

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APPROVAL

This Project titled "Image Based Cattle Nose Print Recognition Technology: A Game-Changer for Individual Cow Identification and Insurance Integrity in Bangladesh's Livestock Industry" submitted by Md. Sayed Hasan and Utsa Kumar Saha to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfilment 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 14/07/2024.

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DECLARATION

We hereby declare that this thesis has been done by us under the supervision of **Mohammad Jahangir Alam, Lecturer (Senior Scale), Department of CSE Daffodil International University.** We also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Cow identification is a critical aspect of livestock management, contributing to efficient record-keeping, insurance, and tracking systems. Traditional methods are labour-intensive and prone to errors. In this thesis, we propose an automated system for cow identification using nose print images. We evaluated several models, including Support Vector Machine (SVM), K-Nearest Neighbor (KNN), VGG16, VGG19, and a custom Convolutional Neural Network (CNN). Our custom CNN model demonstrated superior performance with an accuracy of 99.31% and classification scores (precision, recall, and F1-score) all at 0.99. This high level of accuracy indicates the potential of the proposed system to replace manual identification methods, thereby enhancing the reliability and efficiency of livestock management. Our findings suggest that the custom CNN model is particularly well-suited for this application, offering a robust solution for cow identification that can be integrated into existing livestock management systems in Bangladesh. This research highlights the significance of leveraging advanced machine learning techniques for improving agricultural practices and livestock management.

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KNN	K-Nearest Neighbor
CNN	Convolutional Neural Network
SVM	Support Vector Machine
VGG	Visual Geometry Group

CHAPTER 1
INTRODUCTION

1.1 Overview

Bangladesh's livestock sector is a vital component of the nation's economy, supporting millions of livelihoods and contributing significantly to GDP. With approximately 23.4 million cattle [1], the dairy sector alone is valued at over $2.47 billion USD annually with an 5% growth rate [2], while the meat market is worth over 20.28 billion USD, growing at 9.88% per year [3]. As the demand for dairy and meat products continues to rise, the industry faces challenges in accurately identifying and tracking individual cows, particularly for insurance and healthcare purposes. Traditional methods such as visual inspection or physical tagging are prone to errors and fraud, especially concerning insurance claims [4]. To address these issues, this paper proposes an innovative approach using nose print recognition technology to establish advanced cow identification mechanisms. Similar to human fingerprints, cow nose prints offer a unique biometric signature for each animal, ensuring unparalleled accuracy and reliability [5]. By leveraging modern computer vision and machine learning algorithms, our proposed system aims to detect and recognize cows based on their distinct nose print patterns extracted from images [6] [7] [8]. This solution not only enhances livestock management and traceability but also aids insurance companies in preventing fraud and ensuring transparent claims processing. Furthermore, the system will store comprehensive information about each cow, including medical history, vaccination records, and breed details, providing veterinarians and livestock owners with valuable data for efficient animal care and management. This pioneering effort in biometric cow identification promises to revolutionize livestock management in Bangladesh, driving the sector toward a more secure and efficient future.

1.2 Background and Present State

Effective livestock management relies heavily on the accurate identification of individual cows, which is crucial for health monitoring, insurance, and comprehensive record-keeping. Traditional identification methods such as ear tagging and branding have significant limitations. Ear tags can fall off or get damaged, and branding is a painful process for the animals [9]. These traditional methods also pose challenges in ensuring accurate identification, leading to potential issues in managing livestock records and health care.

Recent advancements have highlighted biometric identification as a promising alternative for livestock management. Specifically, cow nose prints offer a unique and reliable method for identifying individual animals, akin to human fingerprints [5]. Each cow's nose print is distinct and remains consistent throughout its life, making it an effective biometric identifier. Despite its potential, the use of biometric systems for livestock identification in Bangladesh is still in its infancy. Most farmers continue to rely on conventional methods, and there is a notable lack of awareness about the advantages of modern record-keeping and insurance systems. The current landscape of livestock management in Bangladesh underscores the need for innovative solutions. Implementing a system that uses nose print recognition for identifying individual cows can significantly improve health monitoring, ensure timely vaccinations, and streamline overall cattle management. Moreover, integrating this system with insurance and record-keeping services for cattle healthcare can offer substantial benefits to farmers, enhancing the efficiency and productivity of the livestock sector.

1.3 Problem Statement

Identifying individual cows accurately and efficiently in the livestock industry. In particular, countries like Bangladesh with large cattle populations, pose significant challenges. Traditional methods of cow identification like visual inspection or physical tagging are prone to errors and manipulation. Moreover, fraudulent activities, especially in insurance claims underscore the need for robust identification systems. This thesis aims to address these challenges by leveraging nose print recognition technology for precise individual cow identification and tracking.

1.4 Objectives

The objective behind this thesis stems from the critical need to modernize the livestock industry in Bangladesh. There are a lot of demands and problems that need to be solved. Since the livestock industry is important for the country's economy and people's lives, we need new ideas to make it work better. Our main goal with this thesis is to build a system that can accurately recognize cows using nose print recognition technology. This system will help us keep track of cows better and make the livestock industry more efficient. It will also help insurance companies prevent fraud and make sure claims are fair.

1.5 Scope and Limitations

This thesis aims to create a system that can recognize individual cows by their unique nose prints in pictures. The system will involve image acquisition, preprocessing, nose print pattern extraction, feature extraction, and pattern recognition. Additionally, it will propose a system for insurance and tracking the records of cattle. A significant part of the thesis is the development of a user-friendly interface for people to use, which will be integrated with current livestock management systems. Discussions with some farmers revealed that they are not aware of services related to cow insurance and advanced record monitoring systems. Bangladesh presents a promising opportunity for livestock insurance, lacking robust facilities in this area [10]. Therefore, developing a reliable system for them can be highly beneficial for the agricultural sector.

In terms of limitations, most farmers in Bangladesh are not aware of these facilities or how they can significantly streamline their work and reduce hassle. This is especially true for older farmers in rural areas. Many farmers may be resistant to adopting new technology, particularly those in rural areas who are accustomed to traditional methods. Therefore, educational initiatives and support systems will be essential to encourage adoption and ensure the system's effectiveness. Additionally, there is a lack of proper care and vaccination monitoring for livestock in Bangladesh, leading to many farmers missing or forgetting necessary vaccinations and health care measures. If our system is implemented, it will help farmers individually identify each cow, thus improving health monitoring.

1.6 Report Organization

Chapter 1: Introduction**-** This chapter introduces the research, outlining the problem statement, motivation, and objectives. It defines the scope of the thesis, provides a brief description of the findings, and summarizes the key points covered in the report.

Chapter 2: Literature Review**-** Chapter 2 presents an overview of the existing literature relevant to the research. It discusses related works, compares existing solutions, identifies gaps in current knowledge, and concludes with a summary of the chapter.

Chapter 3: Methodology**-** This chapter details the research methodology, including requirement analysis, data collection methods, and analysis techniques. It provides an overview of the thesis management and includes a comprehensive financial analysis.

Chapter 4: Implementation**-** Chapter 4 focuses on the practical implementation of the proposed system. It covers the steps taken to develop the system, including software and hardware components, and the integration process.

Chapter 5: Results and Analysis**-** This chapter presents the results obtained from the implementation. It includes a detailed analysis of the data, discusses the performance of the system, and evaluates its effectiveness in meeting the research objectives.

Chapter 6: Impact on Society, Environment, and Sustainability**-** Chapter 6 examines the broader impact of the research on society and the environment. It discusses how the system contributes to sustainability, the potential benefits for the agricultural sector, and any ethical considerations.

Chapter 7: Conclusion and Future Work**-** The final chapter summarizes the research findings, drawing conclusions based on the results. It also outlines potential areas for future research and suggests improvements to enhance the system's functionality and impact.

1.7 Summary

In summary, this thesis aims to address the challenges associated with individual cow identification in the livestock industry by leveraging nose print recognition technology. By developing a reliable and efficient system for cow identification and tracking. This thesis aims to improve fraud prevention, management, and traceability in the industry in order to support the expansion and sustainability of the cattle industry in Bangladesh.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

Within this section, we look at what other researchers have written about cattle identification systems that use images of their muzzles and other physical characteristics. We examine different ways that researchers have tried to solve the problem of identifying individual cattle accurately.

2.2 Related Works

Several notable studies have contributed to the field of cattle identification using muzzle prints and other biometric features.

Petersen (1923) introduced nose prints as a novel method for bovine identification, akin to human fingerprints [5], with findings from over 350 animals showing unique patterns. The study focused on methodology and observed constancy in patterns despite nose growth.

Mahmoud and Hadad (2015) developed an automatic cattle muzzle print classification system using multiclass support vector machines (MSVMs) [6]. They collected muzzle print images from 52 cattle, preprocessing them with histogram equalization and mathematical morphology filtering for image enhancement and noise reduction. Texture features were extracted using the box-counting algorithm. The system achieved high classification accuracies of 100%, 98%, and 94% for groups of 3, 5, and 10 cattle respectively, based on overall accuracy without reporting detailed precision, recall, or F1 scores.

Sian, C., Jiye, W., Ru, Z., and Lizhi, Z. (2020, May) "Cattle identification using muzzle print images based on feature fusion" introduced a method combining texture features from an improved Weber Local Descriptor (WLD) and Local Binary Pattern (LBP) algorithms for cattle identification using muzzle print images [7]. With a dataset of 900 images from 45 cattle, the authors achieved a peak identification accuracy of 96.5% using Support Vector Machine (SVM) classification on 5x5 sub-regions. They found the improved WLD method using Scharr operators outperformed standard WLD, comparing SVM favourably to K-Nearest Neighbors and Decision Trees, though lacking precision, recall, or F1 score metrics limits comprehensive method evaluation.

Bello, Talib, and Mohamed (2021) present a deep learning approach for cow recognition using cow nose image patterns. Utilizing a database of 4,000 cow nose images from 400 individual cows, the authors employ convolutional neural networks (CNNs) to learn discriminatory features from these images with achieving an accuracy of 95.97% [8]. The authors also demonstrate that accuracy improves with an increasing number of images. However, the study does not provide precision, recall, or F1 scores, focusing primarily on overall accuracy. This omission limits a comprehensive assessment of the models' performance across different aspects. Including these additional metrics would have strengthened their evaluation.

Awad et al. (2013) presented a robust cattle identification scheme using muzzle print images and local invariant features. Highlighting the limitations of traditional methods, they proposed a biometric approach combining Scale Invariant Feature Transform (SIFT) for key point detection and descriptor building with Random Sample Consensus (RANSAC) for robust feature matching [11]. Compared to previous studies, their scheme achieved 93.3% identification accuracy, with a False Acceptance Rate (FAR) of 6.67% and an Equal Error Rate (EER) of approximately 27.4%. The study utilized a database of 15 cattle, with 7 images per animal, focusing on feature-based identification without detailing metrics such as F1 score, precision, or recall.

Tharwat et al. (2014) propose cattle identification via muzzle print images using texture features extracted with Local Binary Pattern (LBP) and dimensionality reduction with Linear Discriminant Analysis (LDA) [12]. They evaluate the method with SVM and other classifiers on a dataset of 217 images from 31 cattle, achieving high accuracy (up to 100%) under various conditions including rotation and occlusion. However, the paper lacks reported F1 scores, precision, and recall metrics for the classifiers used.

Ahmed et al. (2015) proposed a biometric cattle identification system using muzzle prints, employing Speeded Up Robust Feature (SURF) extraction and SVM classification [13]. Achieving 100% accuracy with 20 or more SURF interest points per image, their method surpasses previous approaches. They evaluate on 217 images from 31 cattle, comparing SURF with SIFT and LBP, highlighting efficiency and superior accuracy in cattle muzzle print identification using their proposed SURF-SVM framework.

Kumar et al. (2018) introduced a deep learning framework for cattle recognition based on muzzle point images. The study employs CNN, SDAE, and DBN algorithms achieving accuracy rates of 75.98%, 88.76%, and 95.99%, respectively, with DBN reaching up to 98.99% accuracy using 400 feature sets, but lacks specific F1 score, precision, or recall values for these algorithms [14].

Bello et al. (2020) explore deep learning architectures for cow recognition based on nose image patterns. They compare CNN, stacked denoising autoencoders (SDAE), and deep belief networks (DBN) using a database of 4,000 cow images, achieving recognition accuracies of 98.99%, 96.65%, and 95.97%, respectively. The study lacks detailed metrics like F1 score, precision, and recall, crucial for comprehensive evaluation [15].

The study by Gaber et al. (2016) investigates cattle identification via muzzle patterns using Weber's Local Descriptor and AdaBoost classifier [16]. AdaBoost achieves the highest accuracy of 98.9%, outperforming k-NN and Fk-NN, with additional metrics like recall reported, but F1 score and precision details were not provided.

Monteiro (2016) introduces a novel method for cattle identification via muzzle images, combining SIFT-based feature extraction with graph matching and MLESAC refinement [17]. The approach shows robustness to rotation but lacks quantitative metrics for direct comparison with prior methods using SIFT, RANSAC, LBP, and SURF for this task.

Kumar, S., Singh, S. K., & Singh, A. K. (2017) introduced a muzzle point pattern-based method for automatic cattle identification using texture features like SURF and LBP, combined via weighted fusion [18]. Their approach achieved the highest rank-1 identification accuracy of 93.87%, outperforming PCA, LDA, ICA, and other methods, although lacking precision, recall, or F1 scores for a comprehensive evaluation.

The paper titled "Automatic Fingerprint Classification using Deep Learning Technology (DeepFKTNet)" by Saeed et al. (2022) presents DeepFKTNet-5 achieving 98.89% accuracy on the FVC2004 dataset [19]. Precision, recall, and F1 scores are not provided for any method compared.

Iqbal Hussain et al. (2020) demonstrate the efficacy of deep convolutional neural networks (CNNs) for woven fabric pattern recognition and classification. Their proposed ResNet-50 achieves high accuracy (99.3%) and balanced accuracy (99.1%) in distinguishing plain, twill, and satin weaves, outperforming the VGG-16 model significantly in automated feature extraction and classification from fabric images [20].

Traore et al. (2018) utilize convolutional neural networks (CNNs) to classify microscopic images of epidemic pathogens, achieving 94% accuracy in distinguishing Vibrio cholerae and Plasmodium falciparum. Their CNN architecture includes 6 convolutional layers and 1 fully connected layer, implemented using TensorFlow [21]. Recent research has significantly advanced convolutional neural networks (CNNs) in image classification. For example, Uličný et al. (2016) investigate methods to enhance CNN robustness against adversarial examples and noise, though they primarily focus on techniques like dropout regularization and adversarial training [22]. Sharma et al. (2018) compare AlexNet, GoogLeNet, and ResNet50 on CIFAR and ImageNet datasets, highlighting their performance differences across various architectures [23]. Similarly, Chen et al. (2021) reviews the evolution of CNN architectures, discussing innovations and improvements in image classification methods [24]. Wang et al. (2019) survey CNN development, analysing key architectural elements and advancements over time [25]. Howard (2013) explores CNN improvements for image classification, focusing on technical advancements and strategies for enhancing model efficiency [26]. These studies collectively showcase CNN advancements in image classification and highlight ongoing research into optimizing CNN performance.

2.3 Comparison between existing works

In this section, we compare several prominent studies in the field of cattle identification based on muzzle print images and other biometric features. Each study employs distinct methodologies, ranging from traditional feature-based approaches to advanced deep learning techniques. A comparative analysis is presented in Table 2.3.1, summarizing dataset size used algorithms or techniques and key performance metrics such as accuracy and classification matrix scores where available.

TABLE 2.3.1: COMPARATIVE ANALYSIS WITH PREVIOUS WORK

Paper	**Dataset No. of Cows**	**Algorithm/Techniques**	**Accuracy**	**Classification Scores**
Petersen, W. E. (1923) [5]	350	Practical application and qualitative assessment	Justified that all cows nose prints are unique	N/A
Mahmoud (2015). [6]	52	MSVM	94%	N/A
Sian (2020) [7]	45	LBP + Improved WLD fusion	96.5%	N/A
Bello (2021) [8]	400	CNN	95.97%	N/A
Awad 2013 [11]	15	SIFT+RANSAC	93.3%	N/A
Tharwat (2014) [12]	31	SVM	99.5%	N/A
Ahmed (2015) [13]	31	SURF+SVM	100%	N/A
Kumar (2018) [14]	100	CNN SDAE DBN	75.98% 88.76% 95.99%	N/A
Bello (2020) [15]	400	DBN	98%	N/A

Gaber (2016) [16]	31	AdaBoost K-NN	98.99% 96.8%	N/A
Monteiro, F. C. (2016) [17]	15	SURF	98%	N/A
Kumar (2017) [18]	500	ISVM	90.98%	N/A

2.4 Open Issues

In the progress of making this cow identification using nose prints features, several open issues remain. Such as:

Accuracy and Robustness: While many studies report high accuracy, achieving consistent performance across diverse environmental conditions and varying image qualities remains challenging. Moreover, none of the following studies didn't mention about their models F1 score, average score or Precision score that's why there is no validity that how their model will perform in real testing scenarios.

Scalability: Implementing these technologies on a large scale is a significant challenge for us.

Data Collection and Standardization: There is no proper dataset available for this project. All of the studies were done on a small number of datasets. Gathering high-quality, standardized nose print images from a large number of cows is intensive and requires substantial resources.

Cost and Accessibility: The cost of implementing advanced biometric systems may be prohibitive for small-scale farmers, and ensuring accessibility and ease of use is crucial for widespread adoption

Integration with Existing Systems: Seamlessly integrating biometric identification systems with current livestock management and insurance systems is complex and requires collaboration across multiple sectors.

2.5 Summary

In summary, the literature review highlights the progress made in cow identification systems based on nose print images and other biometric features. These studies highlight various approaches and techniques used in the field of cow's nose pattern identification and tracking. It discusses the significance of accurate identification systems in the livestock industry. It also identifies the limitations of traditional methods such as visual inspection and physical tagging. In particular these studies show, nose print recognition technology holds great promise. Individual cow identification is a dependable and unchangeable method. It also investigates the extraction and analysis of nose print patterns for precise cow identification using computer vision and machine learning methods. Overall, the literature review underscores the importance of adopting innovative technologies to enhance traceability, management, and fraud prevention in the livestock sector.

CHAPTER 3
METHODOLOGY

3.1 Overview

Chapter 3 provides a discussion of the methodology and system’s design employed in the development of the nose print recognition system for individual cow identification. This chapter outlines the steps taken to address the thesis objectives, including requirement analysis, proposed methodology, data collection, system design, thesis management, and financial analysis.

3.2 Proposed Methodology

The proposed methodology for the nose print recognition system encompasses several key components, including image acquisition, preprocessing, nose print pattern extraction, feature extraction, pattern recognition, and database management. Each of these components plays a crucial role in the overall system design and functionality, ensuring accurate and efficient cow identification. Figure 3.2.1 demonstrate the stages of our methodology.

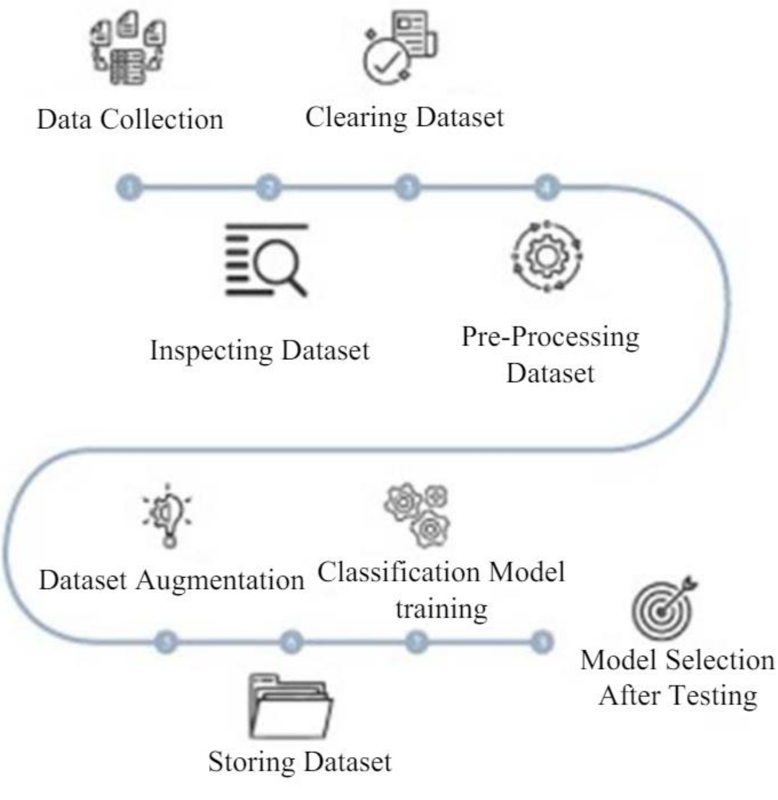

Figure 3.2.1: Methodology

3.3 Data Collection

Data collection is a critical step in developing the nose print recognition system. High-quality images of cow nose prints will be collected using digital cameras or other imaging devices. These images will then be subjected to preprocessing techniques to enhance their quality and prepare them for nose print pattern extraction. The input-output analysis involves defining the input data required for the system (cow nose print images) and the desired output (individual cow identification). There is no decent Dataset on the internet for this kind of work. Especially from the perspective of Bangladesh. So, we collected our dataset from the cow farm called "Sharif Agrovet" which is one of the biggest Cattle farms of Bangladesh called "Sharif Agrovet".

Data Collection Methodology and Equipment

To capture high-quality images, we utilized a Canon 750D DSLR equipped with an 18-55mm lens. The burst shooting mode of the camera allowed us to capture rapid sequences of images, ensuring we captured every nuance of the cow's nose prints with precision and clarity. Each cow was photographed from various angles to capture the unique contours and patterns of their nose prints comprehensively. This meticulous approach was crucial as nose prints can vary subtly based on lighting and perspective. We collected to total 120 cow's 2462 nose images. Figure 3.3.1 shows some sample of our collected raw dataset.

Figure 3.3.1: Collected Dataset Sample

Inspecting Dataset

Not all data come perfect. So many of our images were blurred or were not in perfect angles. These unperfected images can be problematic for building an accurate model. That’s why we inspected all images manually and deleted all blurred images. As a result, we have to completely delete few cows all images as they were not stabled when we took the pictures and pictures came out blurry. After inspecting process, we have total 2092 images of 105 cows.

Cropping

We need only the nose portions of the images so we Cropped the images to isolate the cow's nose region, ensuring consistency and focus for subsequent analysis. Organized the cropped nose images into individual folders corresponding to each cow. Cropping 2092 images manually one by one is a lengthy process. And if we cropped them by auto copping tools it will not be perfect as all nose were not in same position. So, we used Adobe Lightroom to batch edit all images. By using adobe lightroom we can load all images serial by serial as a batch and edit them very efficiently. Figure 3.3.2 represent the batch editing by Adobe Lightroom.

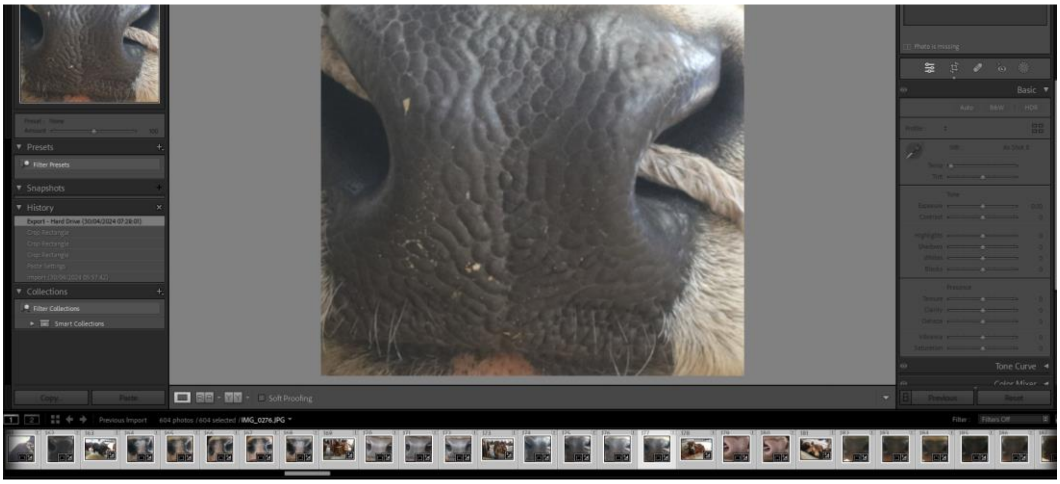

Figure 3.3.2: Batch Cropping by Adobe Lightroom

Organizing the Dataset

We meticulously organized them into individual folders, labelling each set according to the respective cow's identification. To streamline the process, we employed batch rename software, ensuring consistency and ease of access during subsequent stages of analysis and preprocessing. Figure 3.3.3 and Figure 3.3.4 shows our organized and labelled dataset.

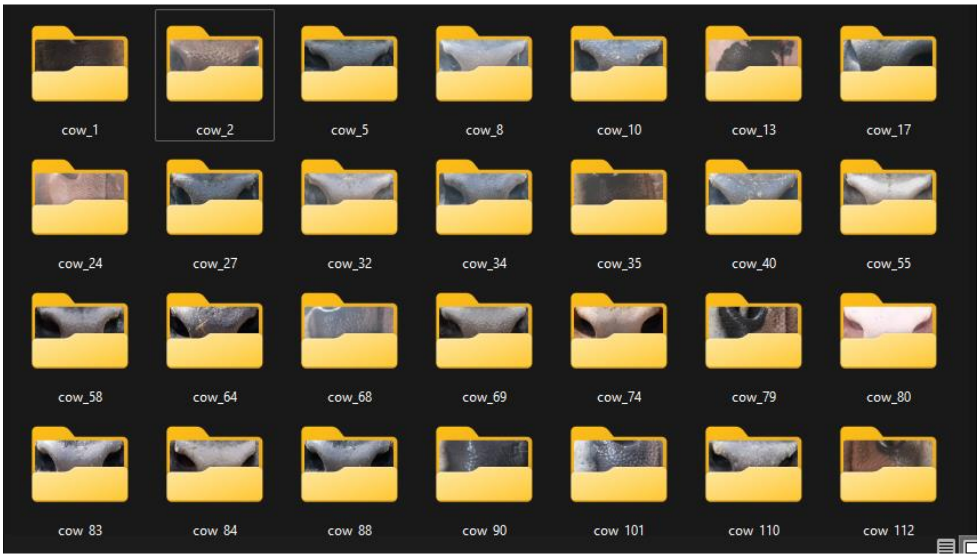

Figure 3.3.3: Each Cow Noses Organized in Specific Folders

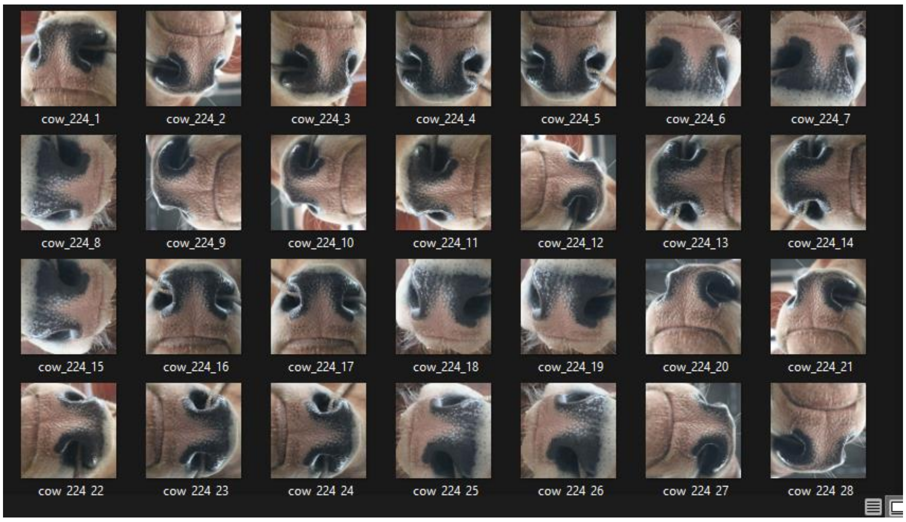

Figure 3.3.4: Each Cow Label with a Given Unique Name to Identify

3.4 Hardware and Software Requirement

Given the extensive nature of our dataset, training the images on free platforms would be highly time-consuming due to their limited computational power. Therefore, we require a robust system equipped with a CUDA-supported GPU to leverage GPU-accelerated computing for efficient model training.

Hardware Requirements

For our project, we selected a powerful system with the following specifications:

- Processor: AMD Ryzen 7 3700X, an 8-core, 16-thread CPU
- Memory: 16 GB RAM
- Graphics Card: NVIDIA GeForce RTX 3060 Ti
- -Video Memory: 8GB

The Nvdia RTX 3060 Ti was chosen due to its impressive capabilities. It contains 4864 CUDA cores and a substantial computing power of 16.2 TFLOPs. This makes it highly suitable for handling large datasets and complex computations required for training our model. The high number of CUDA cores ensures efficient parallel processing, significantly reducing training time and enhancing overall performance.

Software Requirements:

For the software setup, we used Python for the coding part, taking advantage of its rich ecosystem for machine learning and data science. However, Python can sometimes have dependency issues, necessitating a proper environment for smooth operation. To address this, we utilized Anaconda to create a suitable environment and manage dependencies effectively.

The specific software setup includes:

- Anaconda: This is a Python distribution that simplifies package management and environment setup for data science and machine learning projects.
- Python 3.9: This version is essential as it is compatible with the other tools we need.
- TensorFlow 2.10.0: This is the maximum version that supports GPU acceleration. Versions above 2.10.0 do not support the necessary GPU acceleration features for our project.
- CUDA Toolkit 11.2: Required for enabling CUDA support.
- cuDNN 8.1.0: Necessary for deep neural network acceleration.

In addition to these, we installed several other libraries required for our project:

- NumPy: For numerical operations
- Pandas: For data manipulation and analysis
- Matplotlib: For plotting and visualization

- scikit-learn: For machine learning algorithms and tools
- OpenCV: For image processing
- Keras: For building and training neural networks
- Seaborn: For statistical data visualization

By ensuring the right hardware and software setup, we aim to achieve efficient and effective training of our model, leveraging the full potential of GPU acceleration. This setup not only speeds up the training process but also enhances the accuracy and reliability of our system for identifying individual cows through nose prints.

3.5 Project Management and Financial Analysis

Thesis Objectives:

Effective management is essential for the successful execution of the nose print recognition system development thesis. This involves defining thesis milestones, allocating resources, and managing timelines. Figure 3.5.1 is a visual representation of our thesis timeline but Gantt Chart.

Thesis Timeline:

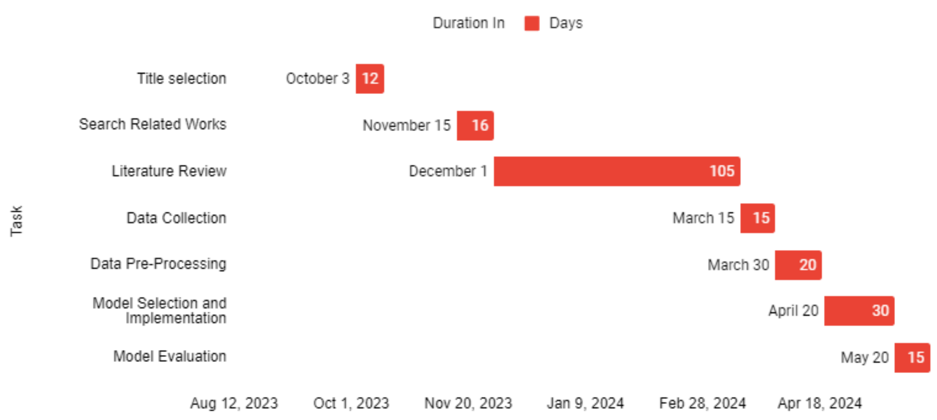

Figure 3.5.1: Timeline Gantt Chart

Resource Planning:

Equipment and Tools:

- High-performance Computers for Development Software (e.g., Anaconda).
- Collaboration Tools (e.g., Google Co-lab/Jupyter Notebook, or project management software)

- Testing Tools (e.g., Manual Testing)

Software and Technologies:

- Programming Language: We need choose a programming language that supports GUI development and has libraries for machine learning model integration. Python is a popular choice due to its extensive libraries for both GUI development and machine learning.
- GUI Framework: We need to select a GUI framework to build our user interface. Some popular choices for Python include Tkinter, Flask, Streamlit. Tkinter is a standard GUI toolkit for Python and is relatively easy to use for simple applications.
- Machine Learning Framework: Since we will develop our model in Python, we likely use a machine learning framework like TensorFlow, scikit-learn. We will ensure that our chosen GUI framework is compatible with these machine learning libraries.
- Image Processing Libraries: We will need libraries for handling image input and output. Python has several libraries for image processing, including OpenCV, Pillow, and scikit-image.
- Data Visualization: To display about the identified cow, we might need data visualization libraries like Matplotlib.

Data and Content:

- Product Data: Capture by us from some Farms near us.
- Product Images: Captured by us from some Farms near us through agreements with Farmers.

Training and Skill Development:

- We have our necessary training and skills in this development, security, and database management.
- We have additional training on specific technologies and tools as needed.

Risk Management:

SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats of a project. Here's a SWOT analysis for our thesis in Figure 3.5.2.

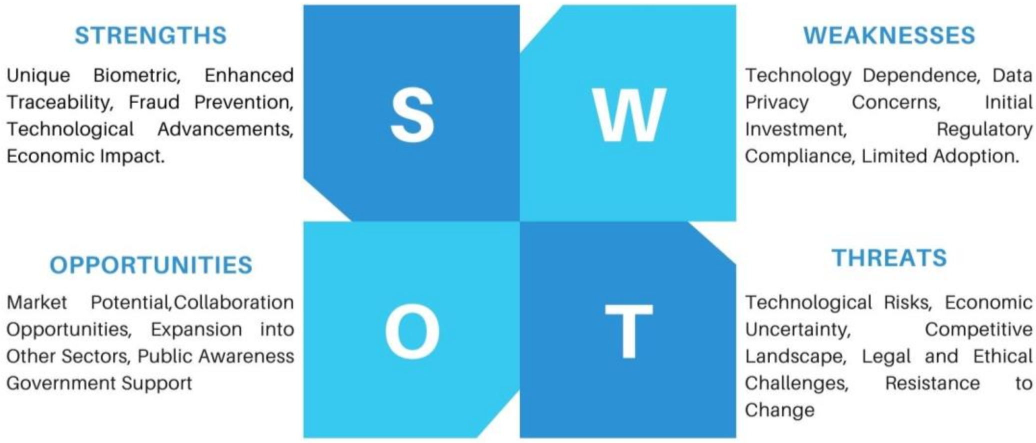

Figure 3.5.2: SWOT Analysis

Financial Analysis:

Financial analysis includes estimating the thesis costs, budgeting. We need a strong Computing System and we need to spend some money on Transportation to collect the data. A detailed potential expense for our thesis is given below in Table 3.5.1.

TABLE 3.5.1: FINANCIAL ANALYSIS

SN	Expense Description	Estimated Cost (BDT)
01	Computing Equipment	2,00,000 Tk.
02	Internet Connection	3,000 Tk.
03	Data Collection and Annotation	5,000 Tk.
04	Travel Expenses	2,000 Tk.
05	Miscellaneous Expenses	500 Tk.

06	Others tools and software’s	5,000 Tk.
	Total Estimated Cost	2,15,500 Tk.

3.6 Summary

This section writing from here. In summary, Chapter 3 outlines the methodology and system design adopted for the development of the nose print recognition system for individual cow identification. Requirement analysis helped define the system's scope and functionalities, while the proposed methodology delineated the steps involved in system development. Data collection, thesis management, and financial analysis were also discussed, providing a comprehensive overview of the thesis's approach and implementation strategy.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

Chapter 4 focuses on the implementation phase of the nose print recognition system. It provides an introduction to the practical realization of the system, data preprocess and training of the models, system testing and evaluation procedures, and a summary of key outcomes from the implementation process.

4.2 Data Pre-Processing

Image pre-processing plays a crucial role in preparing data for machine learning models by enhancing image quality, standardizing inputs, and extracting relevant features. For our cow nose print recognition system, these techniques are essential to ensure accurate and reliable identification of individual cows based on their unique biometric patterns. We used Grayscale Conversion, Histogram Equalization, Gaussian Blur, Image Resizing techniques for image preprocessing.

Grayscale Conversion

The first step in our pre-processing pipeline involves converting the original color images (in BGR format) to grayscale. This transformation simplifies subsequent analysis by focusing exclusively on intensity variations rather than color information [27]. From Figure 4.2.1 we can see this approach is particularly beneficial for our task, where the distinguishing features lie in the texture and pattern of the cow's nose prints

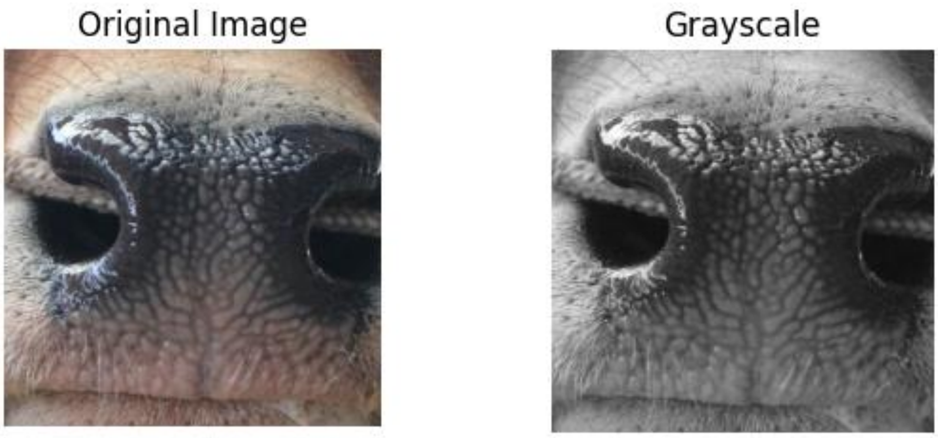

Figure 4.2.1: Grayscale Image Conversion

Histogram Equalization

Histogram equalization enhances image contrast by redistributing pixel intensities across the grayscale spectrum [28]. This technique ensures that subtle variations in nose print patterns become more pronounced, thereby improving the model's ability to discern and classify different individuals accurately. Figure 4.2.2 show the differences between non equalized image vs equalized image and we can see it improved the balance between dark and light zones of the image.

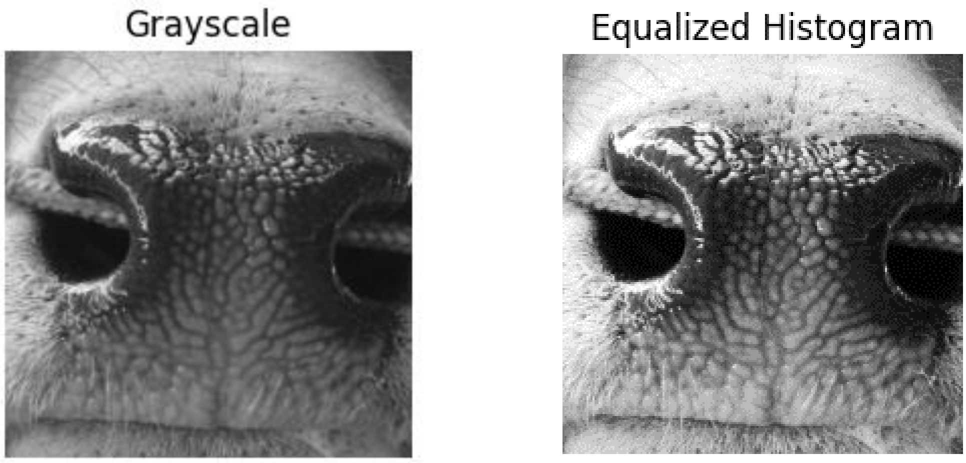

Figure 4.2.2: Histogram Equalization Conversion

Gaussian Blur

To reduce noise and minor variations that could obscure the distinctive features of nose prints [29], we apply Gaussian blur. Figure 4.2.3 shows smoothing technique helps in emphasizing the larger-scale features of the nose prints while suppressing irrelevant details. By doing so, we ensure that the model focuses on the essential characteristics necessary for accurate classification.

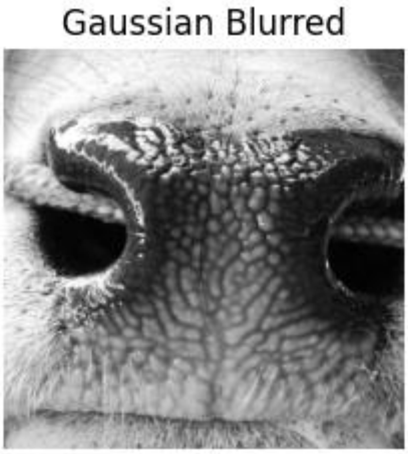

Figure 4.2.3: Gaussian Blur Conversion

Image Resizing

Standardizing the size of our images to 128x128 pixels ensures uniformity across the dataset. This step is critical for neural network models, which require inputs of consistent dimensions to operate efficiently. By resizing the images, we simplify the computational workload and facilitate faster processing without sacrificing image quality. We also made a ,299x299 pixels dataset copy for the models that only can handle 224x224 images like vgg16, vgg19, and 299x299 needs for inceptionV3. Figure 4.2.4 demonstrated these various sizes of images.

Figure 4.2.4: Resized Images sample

Data Augmentation

For data augmentation, a crucial aspect of enhancing model generalization and robustness, several techniques were employed to augment the original dataset of cow nose print images. These techniques included horizontal and vertical flips, random brightness adjustment, and rotation operations. Horizontal flips were applied with a probability of 50%, mirroring the image horizontally. Similarly, vertical flips were applied with the same probability, flipping the image vertically. Random brightness adjustments were performed by converting the images to HSV color space, where the brightness channel's intensity was randomly scaled between 0.7 and 1.3 times its original value to simulate varying lighting conditions. Additionally, images were rotated by 90, 180, or 270 degrees randomly to introduce variations in orientation. Each original image was augmented up to five times to generate a diverse dataset, contributing to improved model training and performance robustness. After Augmentation we have total 12,534 Files images of 105 cows.

Data Splitting

For effective management and utilization of the cow nose print dataset, a robust data splitting strategy was implemented to partition the original dataset into distinct training, testing, and validation subsets. The process began by iterating through each class folder within the input directory, ensuring comprehensive coverage of all dataset classes. Within each class, directories were dynamically created for training, testing, and validation data within the designated output directory structure. To ensure variability and mitigate bias, the files within each class folder were randomly shuffled using Python's random.shuffle() function. Subsequently, the total number of files was calculated, and proportions were allocated for training (70%), testing (15%), and validation (15%) datasets based on these calculations. Files were then allocated to each subset accordingly, ensuring that no file was duplicated across sets. This approach facilitated a balanced distribution of data across training, testing, and validation phases, enabling robust model training, evaluation, and validation for accurate cow nose print recognition. After splitting we got 8,725 of training images and 1,837 testing images and 1,972 validation images (Table 4.2.1). Some of the

TABLE 4.2.1: IMAGE DISTRIBUTION

Number Of Train Images	Number Of Test Images	Number Of Validation Images
8,725	1,837	1,972

4.3 Train Model

Deep learning models for nose print identification leverage convolutional neural networks (CNNs), which are well-suited for image-based tasks due to their ability to automatically learn hierarchical features from raw pixel data. Here's a brief overview of the models we use.

VGG19 Model Implementation

In the initial implementation of the VGG19 model for nose print identification, we utilized a pre-trained VGG19 architecture with its layers frozen except for the last three [30]. This base model, trained on ImageNet, served as a feature extractor, capturing intricate patterns from cow nose print images. We appended a custom classifier consisting of a dense layer with 1024 units, ReLU activation for nonlinear mapping, and a dropout layer to mitigate overfitting. The model was capped with a SoftMax activation layer to output probabilities across our dataset's multiple cow classes. Despite achieving initial validation and test accuracies of 96% and 95%, respectively, the model exhibited poor precision, recall, and F1-scores, indicating suboptimal performance in accurately classifying cow identities based on nose prints. After hyperparameter tuning [31], we modified the VGG19 architecture by increasing the dense layer's units to 2048 and removing dropout to enhance model capacity and prevent information loss during training. The model was trained using a batch size of 8 and underwent 20 epochs, with each epoch taking approximately 48 seconds to complete training. This tuned model demonstrated improved but more balanced performance, achieving validation and test accuracies of 86% and 88%, respectively. The precision, recall, and F1-scores also showed noticeable improvement, with macro-averaged scores reaching 0.62 for precision and 0.51 for recall, indicating better overall performance across multiple classes. This architecture refinement allowed the model to better discern and classify the unique features present in cow nose prints, crucial for accurate individual identification in agricultural and livestock management applications.

VGG16 Model Implementation

The VGG16 model, initially loaded with pre-trained weights from the ImageNet dataset, forms a robust foundation for our cow nose print recognition system[30]. This architecture is renowned for its deep convolutional layers designed to extract intricate features from images. By freezing all but the last three layers, we ensured that the model leveraged its learned representations effectively while customizing the top layers to suit our specific task of classifying cow nose prints into distinct categories. The model architecture begins with convolutional blocks that progressively reduce spatial dimensions while increasing depth, enabling it to capture hierarchical features essential for image classification. Each convolutional layer is followed by a max-pooling layer, optimizing feature extraction while reducing computational complexity. The decision to add a dense layer of 1024 neurons with ReLU activation ensures robust learning of higher-level features extracted by the convolutional layers. Dropout regularization with a rate of 0.2 mitigates overfitting by randomly deactivating some neurons during training, thereby enhancing generalization. Despite achieving an impressive 97% accuracy initially, the model exhibited deficiencies in precision, recall, and F1-score metrics, hovering around 1% across our dataset. This discrepancy underscores the need for further customization and fine-tuning to better accommodate the unique characteristics of cow nose prints. Future iterations will focus on refining the model's top layers, optimizing hyperparameters, and possibly exploring alternative architectures to achieve more balanced and reliable performance in distinguishing individual cows based on their distinctive nose prints. The model was trained using a batch size of 5 and underwent 20 epochs, with each epoch taking approximately 43 seconds to complete training.

SVM Model Implementation

we employed a Support Vector Machine (SVM) model with a radial basis function (RBF) kernel. The SVM is a powerful supervised learning algorithm known for its effectiveness in classification tasks, especially in scenarios with high-dimensional data like image features [9]. The model was trained on features extracted from cow nose print images, which were pre-processed and scaled to improve convergence and performance. Using a grid search with cross-validation, we optimized hyperparameters such as the regularization parameter CCC and kernel coefficient γ\gamma to find the best configuration for the SVM. Feature scaling was crucial to ensure that each feature contributed equally to the model training, and addressing class imbalance was handled using Synthetic Minority Over-sampling Technique (SMOTE), which generated synthetic samples for minority classes in the training data.

KNN Model Architecture and Implementation

The K-Nearest Neighbors (KNN) model was employed to classify cow nose prints, leveraging an image size of 256x256 pixels for consistency. The images were loaded from designated training, validation, and test directories, where each subdirectory corresponded to a specific class label. Each image was flattened into a one-dimensional array to be compatible with the KNN algorithm, which operates in a multidimensional feature space. The KNN classifier was initialized with k=5 neighbors [15], a standard choice balancing bias and variance. The model was trained using the training dataset, where it memorized the training examples, allowing for subsequent classification based on the closest training samples in the feature space. This instance-based learning approach makes KNN suitable for scenarios where the decision boundary is not well-defined, such as the unique patterns found in cow nose prints. Post-training, the model was evaluated on validation and test datasets, and the trained model was saved using joblib for future use. Despite its simplicity, the KNN model provided a baseline for further experimentation and comparison with more complex models.

InceptionV3 Model Architecture and Implementation

For our cow nose print identification system, we utilized the InceptionV3 model, a sophisticated deep learning architecture known for its efficiency and accuracy in image recognition tasks [32]. The base InceptionV3 model, pre-trained on ImageNet, was integrated without its top layers, focusing on a 299x299 pixel input size. We then added a custom classifier comprising a global average pooling layer to reduce the dimensionality, followed by a dense layer with 1024 neurons and ReLU activation. To mitigate overfitting, a dropout layer with a 50% rate was included before the final dense layer, which used a SoftMax activation to output probabilities across our classes. This approach allowed us to leverage the powerful feature extraction capabilities of InceptionV3 while tailoring the final classification to our specific dataset of cow nose prints. The model was trained using a batch size of 8 and underwent 20 epochs, with each epoch taking approximately 89 seconds to complete training.

Proposed Custom CNN Model Implementation

A Convolutional Neural Network (CNN) is a class of deep neural networks that has proven exceptionally effective in image recognition and classification tasks. Unlike traditional neural networks, CNNs automatically and adaptively learn spatial hierarchies of features from input images through the use of convolutional and pooling layers. Convolutional layers apply a set of filters to the input image, enabling the network to detect various patterns such as edges, textures, and more complex structures as the depth of the network increases. Pooling layers, typically max-pooling, then down sample the spatial dimensions of the feature maps, reducing the number of parameters and computation, as well as helping to make the detected features invariant to translation [25]. This ability to learn increasingly abstract representations of the input data through multiple layers makes CNNs particularly suited for tasks like image classification, where distinguishing subtle differences in patterns is crucial. The proposed custom CNN model for cow nose print identification exhibits a streamlined yet powerful architecture tailored to effectively learn and classify distinct patterns in nose prints. The model starts with an initial convolutional layer using 32 filters of size 3x3, employing the rectified linear unit (ReLU) activation function to introduce non-linearity and enhance feature extraction from the input images. Each convolutional layer is followed by a max-pooling layer with a 2x2 pool size, facilitating spatial down sampling to capture dominant features while reducing computational complexity. As the network deepens, subsequent convolutional layers increase in complexity and depth: a second convolutional layer with 64 filters, then a third with 128 filters, each followed by max-pooling to further condense spatial dimensions. This hierarchical arrangement allows the model to progressively learn hierarchical representations of cow nose print features, from simple edges and textures to more abstract patterns indicative of individual cow identities. Following the convolutional layers, the flattened output is passed through fully connected layers. A dense layer with 128 units and ReLU activation serves as a bottleneck to integrate extracted features and facilitate complex decision-making. Dropout regularization with a rate of 0.5 is applied to mitigate overfitting by randomly deactivating a fraction of neurons during training, enhancing generalization to unseen data. The final layer consists of number of classes units with a SoftMax activation function, enabling the model to output probability distributions across all cow classes. This setup ensures that the model can classify each input nose print image into one of the predefined cow identities with high confidence based on learned features. Figure 4.3.1 and 4.3.2 demonstrated the summary and a diagram of our Custom CNN Model.

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 126, 126, 32)      320

 max_pooling2d (MaxPooling2D  (None, 63, 63, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 61, 61, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 30, 30, 64)       0
 2D)

 conv2d_2 (Conv2D)           (None, 28, 28, 128)       73856

 max_pooling2d_2 (MaxPooling  (None, 14, 14, 128)      0
 2D)

 flatten (Flatten)           (None, 25088)             0

 dense (Dense)               (None, 128)               3211392

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 105)               13545

=================================================================
Total params: 3,317,609
Trainable params: 3,317,609
Non-trainable params: 0
```

Figure 4.3.1: Custom CNN Model Summary

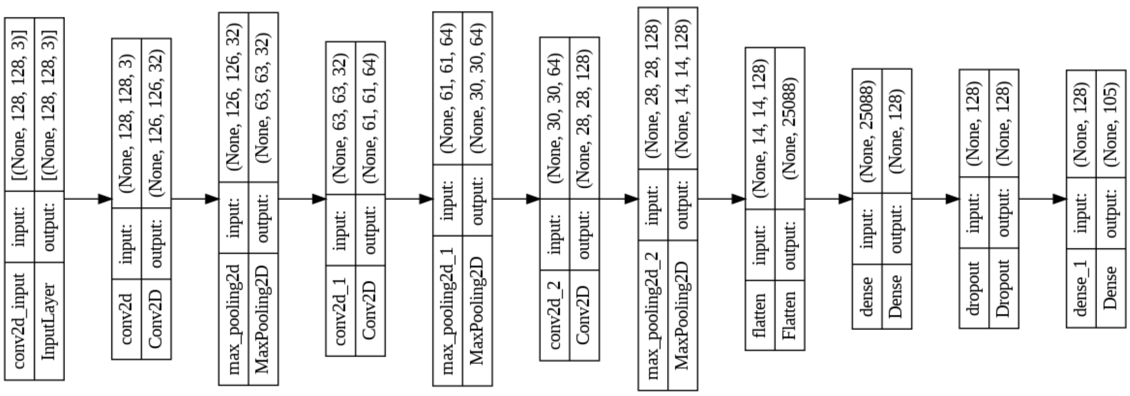

Figure 4.3.2: Custom CNN model Architecture

4.4 Model Evaluation

VGG19 System Testing and Model Evaluation

In evaluating the performance of both VGG19 models, the initial implementation yielded high overall accuracies but lacked precision and recall, resulting in imbalanced classification metrics. Before tuning the it gave validation and test accuracies of 96% and 9%. However, after tuning, the model achieved more balanced results with improved precision and recall scores, especially evident in the macro-averaged F1-score of 0.53 with validation and test accuracies of 86% and 88%. Though accuracy decreased but this has significantly better harmonic mean between precision and recall, crucial for accurately identifying cows based on their nose prints. Support values, indicating the number of samples per class, were adequately represented across the evaluation metrics, ensuring robustness in model performance across various cow breeds and individual identities. These results are very moderate. It's not practically good to predict the cows.

VGG16 System Testing and Model Evaluation

In evaluating the VGG16-based model, we assess its performance using standard metrics precision, recall, and F1-score to gauge its effectiveness in distinguishing between different cow nose prints. These metrics provide insights into the model's ability to correctly identify true positives (precision), capture all relevant instances (recall), and balance precision and recall (F1-score). The support values indicate the number of samples for each class, offering context for the model's predictions across the dataset. Upon evaluation, the model achieved a precision, recall, and F1-score of approximately 0.01, reflecting its initial ability to classify cow nose prints accurately across the dataset. These scores are low too low to predict the cows accurately.

SVM System Testing and Model Evaluation

The SVM model achieved promising results during validation and testing phases. In the validation set, the model demonstrated an overall accuracy of approximately 67.66%. The classification report revealed a balanced performance across precision, recall, and F1-score metrics, with an average precision and recall around 0.68. This indicates that the SVM effectively classified cow nose prints into their respective categories, though there is room for further improvement, particularly in enhancing recall for some classes. Similarly, on the test set, the model maintained a comparable accuracy of about 67.36% with consistent precision and recall metrics.

KNN System Testing and Model Evaluation

The evaluation of the KNN model yielded a validation accuracy of 60.96% and a test accuracy of 60.18%. These results highlight the challenges inherent in cow nose print identification, where unique and subtle patterns must be distinguished across numerous classes. The validation classification report detailed a precision of approximately 0.67 for macro average and 0.70 for weighted average, indicating that while the model was reasonably good at correctly identifying true positives, it faced difficulty with class imbalances and varied data distributions. The recall values were lower, around 0.58 for macro average and 0.61 for weighted average, reflecting the model's struggle to identify all relevant instances, leading to missed identifications. The F1-scores, which balance precision and recall, were around 0.57 for macro average and 0.61 for weighted average, suggesting moderate overall performance.

InceptionV3 System Testing and Model Evaluation

Upon evaluating the model, the InceptionV3-based classifier demonstrated a validation accuracy of 90% and a test accuracy of 92%, indicating strong generalization capabilities. However, the detailed classification metrics revealed room for improvement. The micro-average precision, recall, and F1-score were all recorded at 0.00, suggesting that the model failed to effectively classify individual samples correctly. The macro-average precision, recall, and F1-score were all at 0.04, and the weighted average precision, recall, and F1-score were also at 0.00. These values indicate that while the model achieved high overall accuracy, it struggled with per-class performance, highlighting the need for further tuning and potentially more diverse training data to improve its precision and recall across all categories. This discrepancy underscores the importance of not solely relying on accuracy but also considering other metrics to ensure comprehensive model evaluation.

Proposed Custom CNN Model’s System Testing and Model Evaluation

Upon evaluation, the custom CNN model demonstrates exceptional performance metrics that underscore its efficacy in cow nose print identification. The model achieves a remarkable test accuracy of 99.02% and validation accuracy of 99.31%, indicative of its robust capability to generalize well to unseen data samples. From Figure 4.4.1 we can see our model gave an impressive Train/Validation Accuracy and Loss curve. These high accuracies are complemented by precision, recall, and F1-score metrics, each averaging around 0.99 across all classes. Precision measures the model's ability to accurately predict positive samples, recall assesses its capacity to retrieve all positive instances, and F1-score harmonizes these metrics, providing a balanced evaluation of classification performance. The high values of these metrics signify the model's precision in identifying individual cows based on their unique nose print patterns. Furthermore, the efficiency of the model is notable, with each epoch completing in just 4 seconds, demonstrating its computational efficiency without compromising on accuracy or performance. This efficiency is crucial for real-time applications or scenarios requiring rapid inference times.

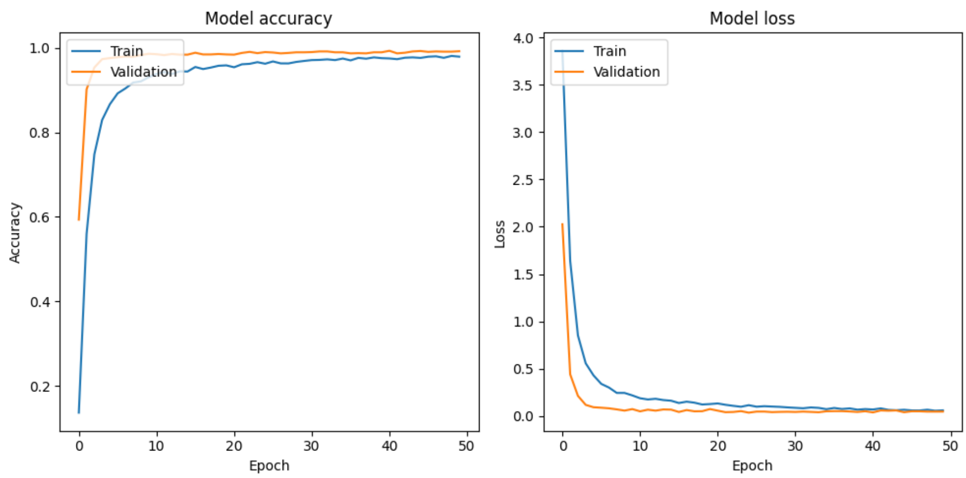

Figure 4.4.1: Proposed Model’s Train/Validation Accuracy and Loss curve

4.5 Summary

Chapter 4 focuses on implementing the cow nose print recognition system. It covers data preprocessing steps like grayscale conversion, histogram equalization, Gaussian blur, and image resizing to standardize inputs. Several deep learning models, including VGG19, VGG16, InceptionV3, SVM, KNN, and a custom CNN, were trained and evaluated. Results showed varying performance metrics across models, with the custom CNN model achieving exceptional precision, recall, and F1-scores, indicating its effectiveness in identifying cows based on nose print patterns. These findings highlight the robustness of deep learning approaches for accurate agricultural and livestock management applications.

CHAPTER 5

RESULT AND ANALYSIS

5.1 Overview

Chapter 5 delves into the results and analysis of the implemented cow nose print recognition system. It explores the experimental findings, performance metrics, and comparative analysis of various deep learning models used for cow identification based on nose print patterns. The chapter provides insights into the effectiveness of each model, highlighting strengths, weaknesses, and implications for agricultural and livestock management applications.

5.2 Experimental Result

The experimental results showcase the performance of various deep learning and machine learning models implemented for cow nose print identification. Each model was evaluated based on its ability to classify unique nose print patterns accurately, essential for individual cow recognition in agricultural and livestock management settings.

VGG19 Model Implementation Results:

Initially utilizing a pre-trained VGG19 model, the system achieved validation and test accuracies of 96% and 95%, respectively. However, precision, recall, and F1-scores indicated imbalanced performance across classes. After hyperparameter tuning, including increasing dense layer units to 2048 and removing dropout, the model exhibited improved validation and test accuracies of 86% and 88%. The refined model showed enhanced precision and recall metrics, with macro-averaged F1-scores reaching 0.53, indicating better overall performance in distinguishing cow identities based on nose prints.

VGG16 Model Implementation Results:

The VGG16 model, also initialized with pre-trained weights, demonstrated initial validation and test accuracies of 97%. However, it showed deficiencies in precision, recall, and F1-scores, reflecting challenges in accurately classifying cow nose prints.

Further customization and fine-tuning are necessary to optimize its performance across diverse cow breeds and individual identities.

SVM Model Implementation Results:

Employing a Support Vector Machine (SVM) with an RBF kernel, the model achieved promising validation and test accuracies around 67.66% and 67.36%, respectively. The SVM demonstrated balanced precision and recall metrics, averaging around 0.68, indicating effective classification of cow nose prints. However, further improvements are needed to enhance recall for specific cow classes and ensure robust performance across varied datasets.

KNN Model Implementation Results:

The K-Nearest Neighbors (KNN) model provided a baseline with validation and test accuracies of 60.96% and 60.18%, respectively. Precision and recall metrics varied, with macro-averaged scores indicating moderate performance in correctly identifying cow nose prints. The model's effectiveness was impacted by class imbalances and varied data distributions, highlighting the need for additional optimization strategies.

InceptionV3 Model Implementation Results:

Utilizing the InceptionV3 architecture, the model achieved high validation and test accuracies of 90% and 92%, respectively. Despite high overall accuracy, precision, recall, and F1-scores indicated room for improvement in class-specific performance. The model's struggle to effectively classify individual samples underscores the importance of refining training strategies and incorporating diverse datasets to enhance performance across all cow classes.

Proposed Custom CNN Model Implementation Results:

The custom CNN model showcased exceptional performance with validation and test accuracies of 99.31% and 99.02%, respectively. Precision, recall, and F1-scores averaged around 0.99 across all classes, highlighting its robust capability to accurately identify cows based on unique nose print patterns. The model's efficiency in inference time further supports its suitability for real-time agricultural applications.

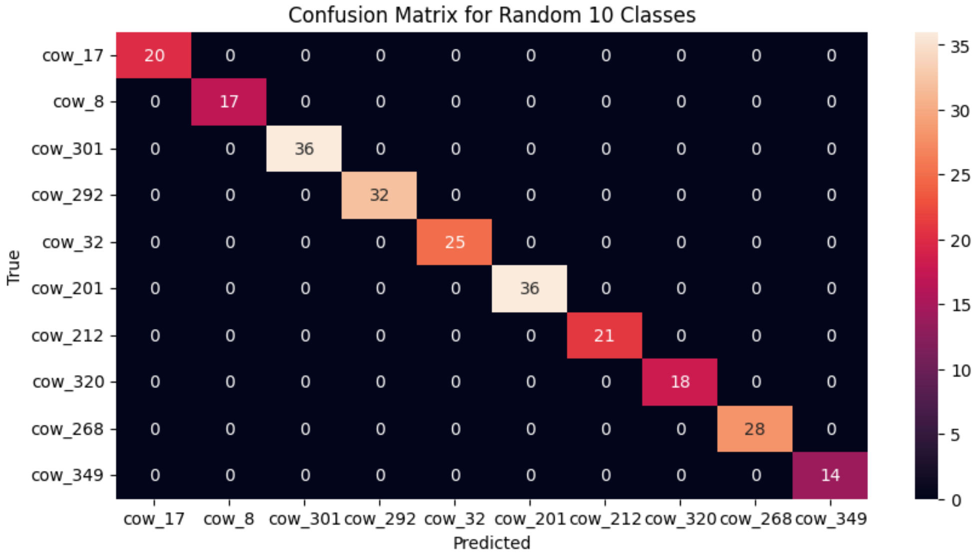

Figure 5.2.1: Custom CNN Model Confusion Matrix

From Figure 5.2.1 Our model gives an accurate confusion matrix. A confusion matrix is a table summarizing a classifier's performance by comparing predicted class labels with actual ground truth labels, revealing where the model confuses predictions. It includes True Positives (TP) for correct positive predictions, True Negatives (TN) for correct negative predictions, False Positives (FP) for incorrect positive predictions (Type I error), and False Negatives (FN) for incorrect negative predictions (Type II error). Derived metrics include Accuracy (overall correctness), Precision (true positives among positive predictions), Recall (true positives among actual positives), and F1 Score (harmonic mean of Precision and Recall).

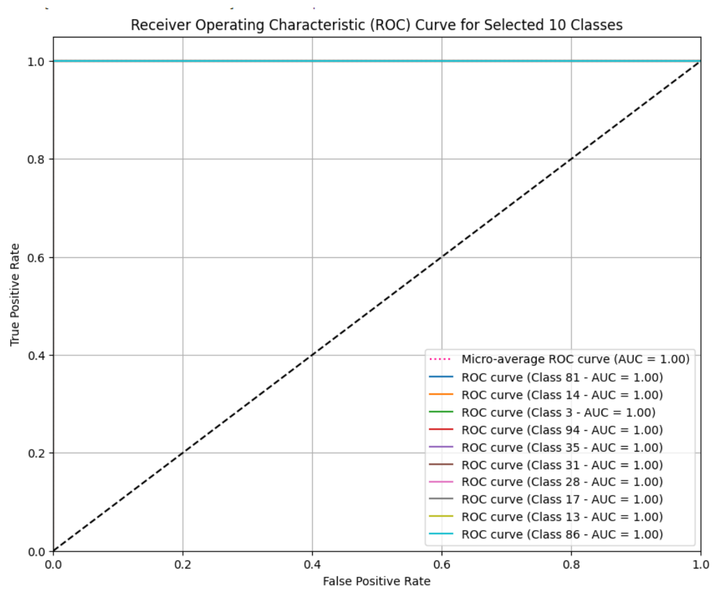

Figure 5.2.2: Custom CNN Model Roc Curve

The ROC (Receiver Operating Characteristic) curve serves as a critical evaluation tool to assess how effectively our classifier distinguishes between different classes. It provides a visual representation by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR), showing how well the model performs across varying discrimination thresholds. In our analysis from Figure 5.2.2, the ROC curve for our model starts at the optimal point, the top right corner. This starting position signifies ideal performance, where all positives are correctly identified without any false positives. From this point, the curve extends as a straight line across the top of the plot. This straight-line segment indicates consistent and high performance across a randomly selected subset of 10 classes. Specifically, this means that for these 10 classes, our model achieves high true positive rates (correctly identifying positives) while maintaining very low false positive rates (incorrectly identifying negatives as positives). This aspect highlights the model's robustness in distinguishing between these classes with minimal confusion or errors. This graphical representation of the ROC curve underscores the model's capability and reliability in practical scenarios. It shows that our classifier effectively and accurately identifies the specified classes, demonstrating strong discriminatory power and performance consistency. This observation is crucial for validating the model's effectiveness in real-world applications, where accurate classification is paramount for decision-making and reliability.

```python
# Function to predict class of an image
def predict_class(img_path, model, label_encoder, IMG_SIZE):
    img = preprocess_image(img_path, IMG_SIZE)
    prediction = model.predict(img)
    predicted_class_idx = np.argmax(prediction)
    predicted_class_name = list(label_encoder.keys())[predicted_class_idx]
    return predicted_class_name

# Paths to saved model and label encoder
model_save_path = r"H:\1.organized\allModel\1.best_CustomCNN_cow_identifier_model.h5"
label_encoder_save_path = r"H:\1.organized\allModel\1.best_CustomCNN_cow_label_encoder.json"
IMG_SIZE = (128, 128)  # Image size as per your preprocessing

# Load the trained model
model = load_model(model_save_path)

# Load the label encoder from the JSON file
with open(label_encoder_save_path, 'r') as f:
    label_encoder = json.load(f)

# Predict the class of a new image
new_image_path = r"F:\Thesis\Final Dataset\cow_343\cow_343_1.jpg"  # Replace with the path to your image
predicted_class_name = predict_class(new_image_path, model, label_encoder, IMG_SIZE)
print(f"The predicted class for the image is: {predicted_class_name}")
```

```
1/1 [==============================] - 0s 120ms/step
The predicted class for the image is: cow_343
```

Figure 5.2.3: Prediction from Test Images

In this demonstration of Figure 5.2.3, we tested with a process of predicting the identity of a cow based on its nose print using our trained Custom CNN model. The image preprocessing steps include converting to grayscale, resizing, histogram equalization, Gaussian filtering, and normalization. The image is then fed into the model for prediction. The model accurately identifies the cow as "cow_343."

- **Image Path:** F:\Thesis\Final Dataset\cow_343\cow_343_1.jpg
- **Predicted Class:** cow_343

This simulation showcases the effectiveness of our model in correctly identifying individual cows based on their unique nose print patterns.

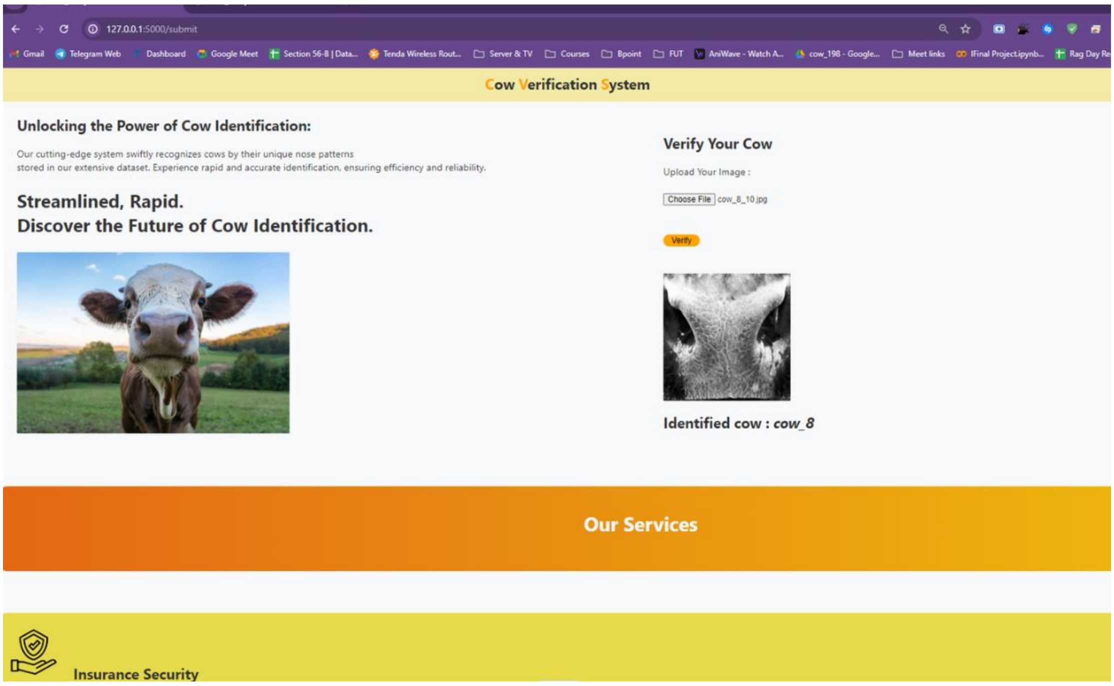

Figure 5.2.4: Prediction from Test Images on Web App

From Figure 5.2.4 we can see the web app we build for cow identification based on nose prints is designed to predict and identify individual cows accurately using a trained TensorFlow/Keras model. It allows users to upload a nose print image, which the model then processes to determine if it matches any of the cows in the dataset. It predicts the cow's identity with high accuracy.

5.3 Performance Analysis

The implementation and evaluation of various models for cow nose print identification highlight significant differences in performance and suitability for the task. The proposed custom CNN model emerged as the most effective, achieving a remarkable validation accuracy of 99.31% and test accuracy of 99.02%. This model demonstrated excellent class discrimination, with average precision, recall, and F1-scores of 0.99, underscoring its ability to accurately classify cow identities based on their nose prints. The model's efficiency is also notable, with each epoch completing in just 4 seconds, trained using a batch size of 8 over 20 epochs.

In contrast, the VGG19 model, initially implemented with pre-trained ImageNet weights and later tuned, showed high validation and test accuracy in its default form (96% and 95%, respectively), but with poor average precision, recall, and F1-scores of 0.01. After hyperparameter tuning, the model achieved validation and test accuracies of 86% and 88%, respectively, with improved but still moderate average precision (0.62) and recall (0.51). The training time for each epoch was approximately 48 seconds with a batch size of 8.

The VGG16 model similarly exhibited high initial accuracy (97% validation and test) but suffered from low average precision, recall, and F1-scores (0.01), indicating a struggle with accurate class distinction. Each epoch took around 43 seconds to complete with a batch size of 5 over 20 epochs.

Traditional machine learning models like SVM and KNN provided moderate performance, with SVM achieving validation and test accuracies of 67.66% and 67.36%, respectively, and balanced precision, recall, and F1-scores around 0.68. KNN had lower validation and test accuracies of 60.96% and 60.18%, respectively, with corresponding precision, recall, and F1-scores around 0.57. These models were less suitable compared to deep learning models.

The InceptionV3 model, despite a strong foundation, achieved validation and test accuracies of 90% and 92%, respectively. However, it exhibited poor precision, recall, and F1-scores of 0.04, indicating challenges in accurately classifying individual cow nose prints. Each epoch took approximately 89 seconds with a batch size of 8. A overview of all of our testing in our dataset and model is shown in the We Table 5.3.1 and a visualisation of the performances is shown in Figure 5.3.1.

TABLE 5.3.1: OUR RESULT ANALYSIS TABLE

Model	Validation Accuracy	Test Accuracy	Average Precision	Average Recall	Average F1-score	Support	Batch Size	Epochs	Epoch Run Time
VGG19 Default	96%	95%	0.01	0.01	0.01	1880	8	20	48s
VGG19 Tuned	86%	88%	0.62	0.51	0.53	1880	8	20	48s
VGG16	97%	97%	0.01	0.01	0.01	1880	5	20	43s
SVM	67.66%	67.36%	0.68	0.68	0.68	1880	-	-	-
KNN	60.96%	60.18%	0.57	0.58	0.57	1880	-	-	-
InceptionV3	90%	92%	0.04	0.04	0.04	1880	8	20	89s
Custom CNN	99.31%	99.02%	0.99	0.99	0.99	1880	8	50	4s

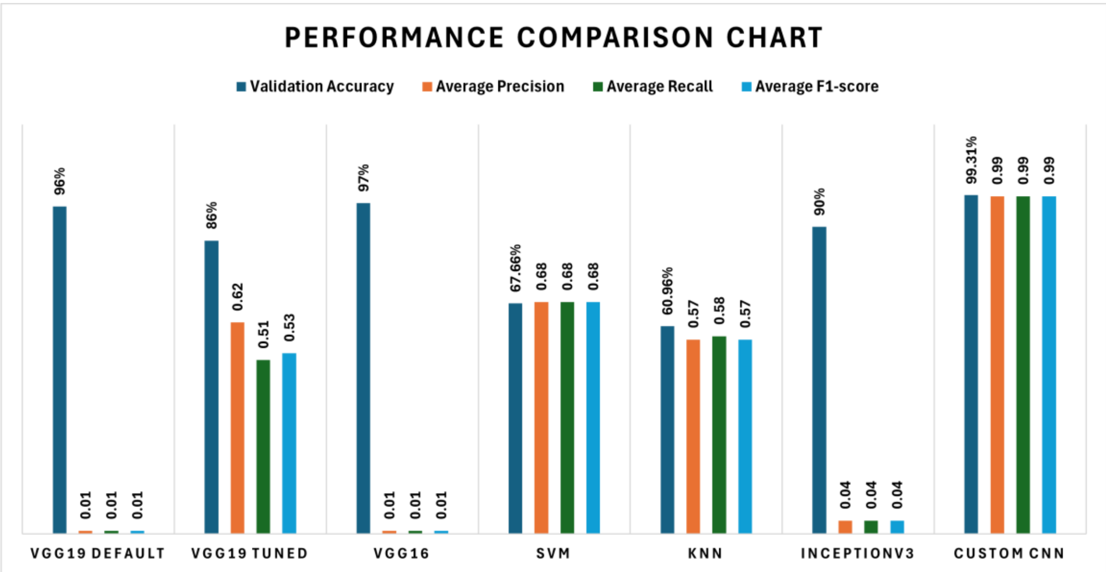

Figure 5.3.1 Model Performance Comparison Chart

5.4 Summary

Overall, the proposed custom CNN model significantly outperforms others, making it the optimal choice for cow nose print identification. The high accuracy and balanced performance metrics, combined with efficient training times, underscore its effectiveness for this application in agricultural and livestock management.

CHAPTER 6
IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

The implementation of a cow nose print identification system significantly enhances the quality of life for farmers and livestock managers. This technology provides a reliable method for tracking and identifying individual cows, ensuring better management of livestock health and productivity. By leveraging biometric identification, it reduces the risk of misidentification, minimizes paperwork, and streamlines administrative processes. Farmers can monitor the health, breeding patterns, and productivity of each cow more accurately, leading to improved herd management. This system also facilitates more efficient vaccination and disease control programs, ultimately promoting better animal welfare and boosting the overall productivity of the dairy and meat industries.

6.2 Impact on Society & Environment

The introduction of advanced livestock identification systems has profound implications for society and the environment. For society, this technology enhances food security by ensuring the traceability of livestock, which is crucial in the event of disease outbreaks or contamination incidents. It also fosters transparency in the livestock industry, building consumer trust in the quality and safety of animal products. Environmentally, the system promotes sustainable farming practices. By accurately tracking and managing livestock, farmers can optimize resource usage, such as feed and water, reducing waste and environmental impact. The ability to monitor the health and productivity of each animal can lead to more informed decisions about breeding and culling, thereby maintaining a balanced ecosystem. Additionally, efficient management of livestock reduces the carbon footprint associated with overstocking and underutilization of resources.

6.3 Ethical Aspects

The ethical considerations of implementing a biometric identification system for livestock are multifaceted. Firstly, the technology ensures humane treatment of animals by providing a non-invasive method for identification, as opposed to traditional methods such as branding or tagging, which can cause distress and injury. This aligns with the principles of animal welfare and ethical farming practices. However, the use of advanced technology also raises concerns about data privacy and security. It is crucial to establish clear guidelines on data ownership, access, and usage to protect the interests of farmers and prevent misuse of information. Additionally, there must be transparency and informed consent in the collection and use of biometric data, ensuring that all stakeholders are aware of and agree to the processes involved.

6.4 Sustainability Plan

To ensure the long-term sustainability of the cow nose print identification system, several strategies must be implemented:

- **Continuous Improvement:** Regular updates and improvements to the technology based on user feedback and advancements in biometric identification will maintain its relevance and effectiveness.
- **Training and Support:** Providing comprehensive training and ongoing support to farmers and livestock managers will facilitate smooth integration and maximize the system's benefits.
- **Collaboration:** Partnering with agricultural organizations, government bodies, and research institutions will foster innovation and ensure the technology aligns with industry standards and regulatory requirements.
- **Scalability:** Designing the system to be scalable will accommodate growing livestock populations and expanding farm operations, ensuring it remains useful for both small-scale and large-scale farms.
- **Environmental Stewardship:** Promoting practices that reduce environmental impact, such as efficient resource management and waste reduction, will enhance the sustainability of livestock farming.

6.5 Summary

The cow nose print identification system represents a significant advancement in livestock management, offering numerous benefits to life, society, and the environment. It improves the accuracy and efficiency of tracking individual cows, enhances animal welfare, and supports sustainable farming practices. Ethical considerations and a robust sustainability plan are essential to ensure the responsible implementation and long-term success of this technology. By fostering collaboration and continuous improvement, this system can contribute to a more sustainable and transparent livestock industry, ultimately benefiting farmers, consumers, and the environment.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

In conclusion, the evaluation of various deep learning and traditional machine learning models for cow nose print identification highlights the superiority of deep learning approaches, particularly the custom CNN model. With a validation accuracy of 99.31% and a test accuracy of 99.02%, coupled with average precision, recall, and F1-scores all at 0.99, the custom CNN demonstrates exceptional capability in accurately classifying individual cows based on their unique nose print patterns. This robust performance underscores the effectiveness of deep convolutional neural networks in capturing and leveraging intricate features essential for precise agricultural and livestock management applications.

7.2 Further Suggested Works

Moving forward, several avenues for future research and development are suggested to enhance the current cow nose print recognition system. Firstly, expanding the dataset to include a broader diversity of cow breeds and nose print variations could improve model generalization and robustness. Secondly, exploring ensemble methods or hybrid architectures that combine the strengths of different deep learning models could potentially further boost classification accuracy and mitigate any remaining class imbalances. Additionally, investigating real-time deployment scenarios and optimizing model inference times could facilitate practical applications in livestock management settings. Lastly, continuous monitoring and updating of the model with new data would ensure its efficacy over time, adapting to evolving patterns and trends in cow nose prints.

7.3 Limitations

Despite the promising results, this study has several limitations. Firstly, the dataset's size and diversity may not fully represent all possible variations in cow nose prints, potentially limiting the model's ability to generalize to unseen or more diverse samples. Secondly, the computational resources required for training deep learning models, especially those with extensive architectures like the custom CNN, may pose practical challenges in resource-constrained environments. Moreover, as with any biometric identification system, there are ethical considerations regarding data privacy and consent, which must be carefully addressed to ensure responsible implementation and usage. Finally, while efforts were made to minimize bias and ensure transparency in reporting results, inherent biases in dataset collection or preprocessing steps could influence model performance and interpretation. These limitations highlight the need for continued research and development in balancing technological advancements with ethical considerations, aiming towards more robust and inclusive solutions for agricultural and livestock management applications.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: Image Based Cattle Nose Print Recognition Technology: A Game Changer for Individual Cow Identification and Insurance Integrity in Bangladesh's Livestock Industry

Students ID: 201-15-13789

And

Students ID: 201-15-14237

CO Description for FYDP

CO	CO Descriptions	PO
	Phase -I	
CO1	Integrate recently gained and previously acquired knowledge to identify a **Cattle Nose print Identification** problem for the Final Year Design Project.	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goals for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
	Phase -II	
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**

CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**
CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, and CO3	Our thesis requires data collection from the outfield then training them according to machine learning model and also, we need research knowledge for it which covers K4 and K8	**Page no:** [13, 05-08] **Section:** [3.3, 2.2, 2.3]
				Our thesis needs to write codes for the model training process and we need to have mathematics knowledge to understands the algorithm that covers K6, K3 and K2	**Page no:** [21-29] **Section:** [4.1-4.3]
				Our thesis is for the welfare of Bangladeshi farmers and we want to design a good system for them that covers K7 and K5	**Page no:** [01-03] **Section:** [1.1, 1.2, 2.4]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2	We need a proper dataset to train our models but there is no properly available dataset that meets our requirements, especially in Bangladesh's perspective.	**Page no:** [13] **Section:** [3.3]

3.	**EP3: Depth of analysis required**	Yes	CO2	We need images of cow noses from various angles. We need to take pictures of at least 5 different angles of the nose of each cow and at least 1 for test purposes. Then for the model train purpose we need to have a Strong Computer System that has a strong computing power. There are various models that can be used to train our dataset.	**Page no: [**13] **Section:** [3.3]
4.	**EP4: Familiarity of Issues**	Yes	CO3	Our thesis Domain is Agriculture field. So, we are not familiar with this field as we are CSE students. We already talked with some farmers about this. And our thesis has a great impact on the Agriculture Field. More specifically on the Livestock farming industry.	**Page no: [**01-02] **Section:** [1.2]
5.	**EP5: Extends of application codes**	Yes	CO3	There are various algorithms to train our dataset. These algorithms can be tuning and we can also add more techniques in data preprocessing to ensure maximum result	**Page no: [**25-32] **Section: [**4.3,4.4]
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	Yes	CO3	We already talked with some farmers and they are not aware about this kind of service. After knowing some basic information, they showed their interest in it.	**Page no: [**02] **Section:** [1.2]
7.	**EP7: Interdependence**	Yes	CO3	There are multiple interdependent components in our project. These include tasks like collecting data, analysing it, creating front-end applications, undertaking predictive analysis, and training machine learning models.	**Page no: [**12] **Section:** [3.2]
8.	**EP8: Financial Analysis**	Yes	CO4	For collecting data, we need to go outside so there is a transportation expense and we need a powerful system that can train our model.	**Page no: [**18-20] **Section:** [3.5]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	My project leverages high-performance computing, GPUs, and deep learning frameworks to advance cattle nose print recognition technology. Utilizing datasets and a custom CNN model, we ensure precise identification. Ethical considerations are integrated to address data privacy, contributing to improved livestock management and insurance integrity in Bangladesh.	**Page no:** [15-17, 13-15, 31] **Section:** [3.4,3.3,4.4]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	Yes		We built a Custom CNN model which is very efficient and accurate.	**Page no:** [31] **Section:** [4.4]

4.	**EA4: Consequences for society and the environment**	Yes		My project focuses on cattle nose print recognition technology, which enhances livestock management by ensuring accurate identification of individual cows. This technology improves insurance integrity, reducing fraud and ensuring fair compensation. By supporting efficient and reliable identification, it contributes to better herd management and health monitoring, leading to increased productivity and profitability. These efforts promote sustainable agricultural practices and strengthen the livestock industry in Bangladesh, ultimately enhancing food security and economic stability.	**Page no: [**01-03] **Section:** [1.1-1.5]
5.	**EA-5: Familiarity**	Yes		This project extends current research by exploring a novel approach to cattle identification using nose print recognition technology. It introduces new methodologies and conducts a detailed comparative analysis, showcasing advanced techniques and providing fresh insights into the field of livestock management and insurance integrity.	**Page no:** [05-10] **Section:** [2.2]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses effective livestock management by integrating advanced identification technology and insurance oversight, ensuring meticulous planning, resource allocation, and system optimization for enhanced cattle identification and insurance processes throughout the project lifecycle.	**Page no: [**17-19] **Section:** [3.5]
2	CO9	Yes	The project upholds ethical practices by prioritizing data privacy, ensuring transparency in the use of livestock information, providing accurate and fair identification results, respecting local agricultural practices, and promoting accessibility for all farmers. These measures foster trust, transparency, and integrity among stakeholders in the livestock industry.	**Page no: [**41] **Section:** [6.3]
3	CO10	Yes	We collected our dataset of cattle nose prints and developed machine learning and deep learning models. These tasks were divided among our team members, ensuring effective collaboration and the successful completion of our project goals.	**Page no:** [12 -15] **Section:** [3.2, 3.3]
4	CO12	Yes	The project's dedication to continuous learning and adaptation is reflected in its comprehensive data collection of cattle nose prints, rigorous statistical analysis, meticulous methodology development, and thorough experimental results. This showcases our commitment to staying updated and refining techniques to address modern challenges in livestock management and insurance integrity.	**Page no:** [12, 33] **Section:** [3.2, 5.2]

Image Based Cattle Nose Print Recognition Technology: A Game Changer for Individual Cow Identification and Insurance Integrity in Bangladesh's Livestock Industry

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