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A Deep Learning Biometric Cattle Identification System to Combat Cattle Rustling in Nigeria

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Abstract

Cattle rustling remains a serious threat to livestock farming, food security, food supply, and economic stability in Nigeria. Traditional cattle identification methods like ear tagging and branding are prone to damage and offer limited durability and accuracy. This study presents reliable and non-invasive cattle biometric identification system based on deep learning that utilizes muzzle-print images to address these limitations. Muzzle prints are similar to human fingerprints that are unique and tamper-proof. These make muzzle prints a viable biometric trait for cattle identification. A dataset comprised of 1,038 muzzle-print images from 70 cattle collected from two local farms and the Zenodo public repository was preprocessed through normalization, resizing and reduction of noise. Data augmentation techniques such as rotation, zooming, and brightness were used to increase dataset diversity. The ResNet-50 convolutional neural network was fine-tuned for muzzle print classification due to it known strong performance in image recognition. The model effectively identified cattle under varying environmental conditions to achieve an accuracy rate of 99.9%. Limited data availability, variability in image capture conditions and hardware constraints were some of the challenges encountered during the implementation stages.

Keywords: Cattle rustling, biometric identification, muzzle prints, ResNet-50, and deep learning.

1. Introduction

Despite the acceptance, roles, and importance of emerging technologies such as artificial intelligence, machine learning, and internet of things technologies, especially in industry, and agriculture, many economic sectors in Nigeria continue to rely on traditional systems and techniques for their operations. This encompasses the use of naked eyes, surveillance security, armed guards, and local vigilante groups to detect and prevent crimes such as insurgency, crises, cattle rustling and cattle management. Agriculture stands as Nigeria's second-largest source of income after crude oil, with about 50% of the teeming population depending on various agricultural businesses, such as livestock, marketing, and cropping (Adamgbe et al., 2020). However, the farming system faces several challenges, including low yields, farms destruction by cattle, and cattle rustling. Cattle rustling has a long history and has posed an extended security and economic challenge in East African countries such as Kenya, and it is increasingly becoming a significant threat to West African countries like Nigeria and Cameroon (Aucoin & Mahmood, 2017). Cattle rustling is not confined to developing countries like Kenya and Nigeria because it also occurs in developed countries like Australia and the United States (Malnekoff, 2013; as cited in Okoli, 2019). Cattle rustling has evolved from a minor activity manageable by police into a well-planned, and coordinated commercial enterprise in many communities in Nigeria (Bunei et al., 2016). A cattle rustling occurs when there is a systematic and coordinated plan to forcibly take away cattle from others for financial gain. It can also be defined as "a prevailing form of rural banditry in contemporary Africa" (Okoli, 2019). With the rising number of reported cases of cattle rustling

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across West African countries, particularly Nigeria, there is a growing concern about the effectiveness of the existing methods for deterring cattle rustling. Numerous incidents of cattle rustlers attacking herders' settlements and farms have resulted in the destruction of lives and properties, as well as the rustling of approximately 7,000 cattle from October 2013 to March 2014 in Katsina State of North Western Nigeria alone (Bashir, 2014). Similarly, in North Western Nigeria from 2011 to 2021, around 250,000 livestock were rustled resulting in the death of 12000 individuals, displacement of 50,000 more and the destruction of about 120 villages (Rufa'i, 2021). Moreover, a group of bandits killed approximately nine (9) individuals and rustled hundreds of cattle in Dansadau town of the Maru Local Government Area in Zamfara State on Tuesday, May 18, 2021. The armed bandits were estimated to number around one hundred and fifty (150), and the rustled cattle were found to exceed three hundred (Maishanu, 2021). According to the Global Initiative on Cattle Rustling, Cattle rustling is linked to numerous other violent incidents resulting in thousands of deaths and significant displacement, exacerbates tensions and violence in the affected areas that is often intertwined with disputes between farmers and herders (Madueke, 2023). For example, associated with cattle rustling are various crimes, including conflicts, rapes, human displacement, and the destruction of livelihoods, lives, properties, and communities (Olaniyan & Yahaya, 2016). Additionally, the proceeds from cattle rustling have significantly fueled the levels of insurgency and banditry in Nigeria and across Africa (Okoli, 2019). Several attempts and recommendations have been put forth by both state and non-state actors to combat this issue in Nigeria, but they have yielded limited success (Rufa'i, 2021). The limitations of these recommendations and conventional methods used in curbing cattle rustlings are evident in the increasing number of reported cases and the closure of cattle markets, particularly in Zamfara and Katsina states, to prevent the trading of unidentified rustled cattle (Ejechi, 2023). The rustlers' ability to move or sell the rustled cattle is what makes this criminal activity lucrative and sustainable.

2. Related Works

Cattle identification is critical in deterring the movement and trade of rustled cattle across markets. Researchers have suggested various methods of cattle identification, the overall goal of which is the identification of cattle. Workable identification methods are needed in the view of a disease outbreak, managing vaccines, verifying insurance claims, ownership as well as preventing cattle rustling. There are three major categories of cattle identification, traditional, technological, and biometric (Akinsolu et al., 2021; Kumar et al., 2017). Figure 1 summarizes various cattle identification methods, including an improved version of the approach proposed by Awad *et al.* (2013).

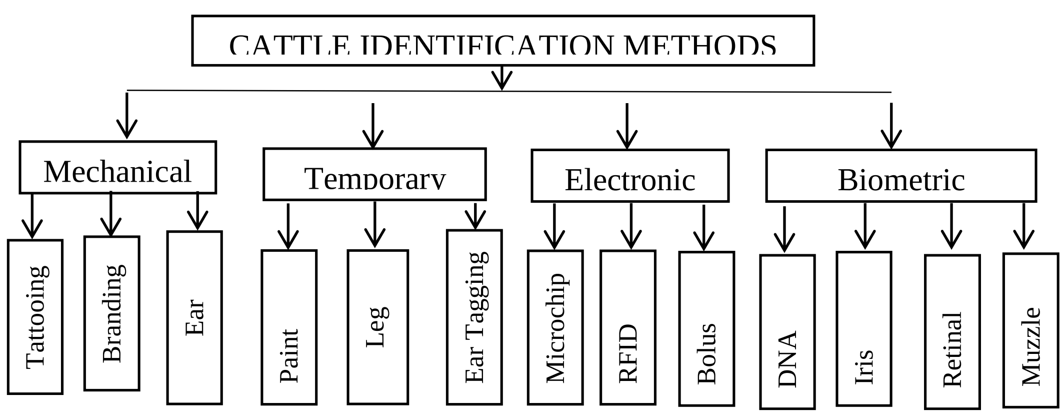

Figure 1: Methods of Cattle Identification

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2.1.1 Traditional Cattle Identification Method

Traditional cattle identification methods have been used for years in managing livestock and allowed farmers or researchers to identify a single cattle based on its outward appearance through natural markings, coat color and pattern, shape, horns, and brands (Cihan et al., 2023). Most notably, branding-hot iron methods can be administered to the hides to display cattle origin and ownership (Awad, 2016). Other conventional techniques include tattooing, ear notching, ear tagging, and electrical methods (Bodkhe et al., 2018). However, According to Awad & Hassaballah (2019), branding poses an ethical issue because it is painful and causing damage to the hide permanently, thus reducing the value of the cattle. Similarly, Tattooing basically gives permanent scars like branding but is less invasive (Oliveira et al., 2024). Ear notching involves a certain type of cut on the cattle ear in a specific shape. Notching is mainly used in locations where ear tagging is often lost, damaged, or removed. Ear tagging refers to a small number on the tag attached to the cattle ear as illustrated in Figure 2 and Figure 3 for sample traditional cattle identification methods.

(a) (b) (c)

Figure 1: (a) Ear notching. (b) Ear tattooing. (c) Ear tag with RFID (Adapted from Award, 2016)

Figure 2: Different Traditional Methods of Identification (Adapted from Bodkhe et al., 2018)

Most of these methods have some advantages and disadvantages. The common advantages of the traditional methods are simplicity and low cost (Zhang et al., 2023); a mutual disadvantage is being subject to duplication, ethical concerns, loss, damage, and fraud, which renders them ineffective (Ahmad et al., 2022). These drawbacks such as rustlers' ability to damage, duplicate, and remove any identity have rendered the traditional methods ineffective in deterring cattle rustling in Nigeria.

2.1.2 Radio Frequency Identification

The failure of conventional methods and technological advancement has paved the way for Radio Frequency Identification (RFID) to emerge in cattle identification. RFID, with its reader, captures a unique identification number attached to the cattle on a cattle ear, which gets traced and

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automatically identified by the reader (Chien & Chen, 2018). RFIDs have overcome some of the drawbacks of traditional methods by improving speedier identification, management, and accuracy in monitoring and preventing cattle theft (Ajisegiri et al., 2023) . However, the requirement for cattle to pass through certain checkpoints or areas before the RFID can track and identify them has made the technology unsuitable for deterring cattle rustling in countries like Nigeria, where rustlers are capable of bypassing many towns, roads, and checkpoints (Ibrahim et al., 2016). Refer to Figure 4 for Architecture of the RFID system for cattle identification System.

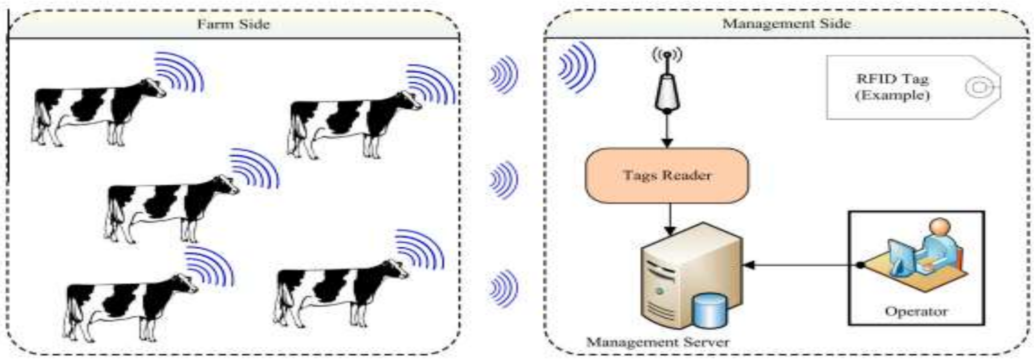

Figure 3: Architecture of the RFID system for cattle identification (Source: Awad, 2016)

2.1.3 Biometric Cattle Identification

Due to the several limitations evident in both traditional and technological approaches, biometric cattle identification has been considered by researchers because it has provided fool proof solutions by addressing most of the issues associated with loss, damage, tampering, and duplication (Shojaeipour et al., 2021). Biometric identification systems use distinctive physiological traits such as muzzle patterns, face image, and iris patterns, visual patterns, retinal vascular to offer a robust, non-invasive alternative that enhances cattle traceability and management while protecting their welfare (Cihan et al., 2023). Other biometrics includes the pattern of retinal vascular structures (Awad, 2016). However, the biometric cattle identification system faces several challenges: cattle behaviour, light conditions, image quality, and the camera's positioning (Qiao et al., 2019). Other issues that are equally important to consider for better practical solutions include processing time and cost (Cihan et al., 2023). The following sections briefly explain biometric cattle identification methodologies.

2.1.3.1 Facial Recognition Methodologies

Facial recognition system has been adapted in cattle recognition. The advancement in machine learning and computer vision have help some researchers to develop a systems capable of real-time classification and detection of cattle faces in dynamic situations such as grazing areas (Kumar et al., 2018). Facial recognition system provides better accuracy result when dealing with cattle in moving freely in a real-time and capturing the entire face is less stress than other methods such as iris scan and retina patterns (Bergman et al., 2024). Facial recognition utilizes unique features of cattle face that are also stable throughout cattle lifetime like muzzle prints (Kusakunniran et al., 2023). However, facial recognition also has its limitations in terms of light and other environmental factors.

2.1.3.2 Iris Recognition Methodologies

Another non-invasive and reliable emerging cattle identification method is iris scans. Like other biometrics system of identification, the iris cattle identification systems also rely on the uniqueness and permanent stability of the iris throughout cattle lifetime (Larregui et al., 2019). This uniqueness and stability of the iris make it very suitable for recognizing individual cattle for different purposes. Iris-based cattle identification involves many stages starting with acquiring a high quality images using visible-light camera to segmentations and analysis (Saygılı et al., 2024). However, acquiring proper images and correct segmentation of iris is tedious and requires special equipment considering the uncooperative nature of cattle. Larregui (2019) observed that acquiring high-quality iris images remain a major challenge despite the advancement of technologies due to the uncooperative nature of cattle such as cattle movement, technological factors such as specialize equipment and environmental factors light. These and other barriers such as the cost affect the widespread adoption of iris identifications systems.

2.1.3.3 Retinal Recognition Methodologies

Retinal biometric identification has also emerged as one of the highly secured and reliable methods for identifying cattle due to the uniqueness of retinal vascular patterns of each cattle and its stability throughout cattle lifetime (Mustafi et al., 2021). The retinal vascular pattern biometric systems of cattle identification depend on retinal image recognition (RIR) for identification due to the uniqueness of retinal vessels (Gonzales et al., 2008) . However, obtaining a comprehensive retinal image datasets is a tedious process, and the reported performance measures lag behind other biometric systems, such as those based on iris or muzzle patterns (Lu et al., 2014) . Additionally, lack of standard and reliable methods of capturing correct and proper retinal images is a major drawback that affects the widespread adoption of retinal biometric system of identification (Allen et al., 2008).

2.1.3.4 DNA Recognition Methodologies

DNA-based biometric identification systems is another important modern livestock identification system that offers unparalleled reliable and precise method of cattle identification (Baptista et al., 2021). DNA-based approaches leveraging the uniqueness of genetic which scientifically proven to be robust, reliable and tamper-proof alternative method of identification (Gallinat et al., 2013). There are various DNA-based methods that have been used by researchers to identify animals such as cattle. However, the cost, complexity and requirements for extraction of DNA sample and it analysis is one of the major barriers preventing its widespread adaption despite its high accuracy rate (Baptista et al., 2021). Moreover, environmental contaminants, sample degradation, and inhibitors are other factors that may compromise the quality of DNA (Meiklejohn et al., 2021).

2.1.3.4 Muzzle prints Recognition Methodologies

Muzzle prints are a dermal trait of cattle analogous to fingerprints in human beings (Baranov et al., 1993). They have been verified as a unique identifier for cattle since 1921 (Petersen, 1922). This is due to the arrangement and structure of grooves and ridges on the noses of cattle (Bello et al., 2020). The research demonstrates that the patterns remain consistent throughout the cattle's lifetime, while the size of the muzzle prints may increase. This was reestablished by Islam *et al.,* (2024) in their recent research where they verified that cattle muzzle prints recognition works similarly to fingerprint identification in humans by collecting a dataset of over 32,000 images from

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826 cattle, achieved a remarkable identification accuracy of 98.7%. Refer to Figure 5 for cattle muzzle patterns.

Figure 4: Cattle Muzzle Patterns (Source: Li et al., 2022)

2.2 Evolution of Cattle Identification

Cattle identification keeps changing with time, and research significantly incorporates different methodologies, strategies, and technologies to improve efficiency, security, and precision. Most traditional methods are being replaced or supplemented by the rapid advancement in technology. For example, Radio Frequency Identification (RFID) and GPS technologies are being used for tracing cattle, while Scale Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF) are used in feature detection in image-based methods. Convolutional neural networks (CNNs), a deep learning approach, have shown great potential in biometric cattle identification recently. The following sections highlight the contributions of the methodologies in the area of biometric cattle identifications.

2.2.1 RFID and GPS Technologies

Various technologies exist for tracking and identification to improve livestock security and prevent cattle rustling in developing countries like Nigeria and Kenya. Two of these technologies are Radio Frequency Identification (RFID) and Global Positioning System (GPS) technologies. Integrating GSM communication systems and GPS technologies has been used to monitor the location or movement of cattle to prevent cattle rustling. For example, a GPS/GSM collar prototype was developed by Tangorra *et al.* (2013) with the sole aim of fighting cattle rustling in Italian grazing areas. The developed prototype was able to improve tracking accuracy, battery life, and animal comfort when wearing the collars. The integration of the SMS communication has enabled the system to send real-time information about unauthorized movement of cattle out of a virtual fence or an attempt to temper with the collars for the farmers to provide a timely intervention to prevent cattle rustling. However, the infrastructural requirement is a major challenge for implementing such system in Nigeria. Additionally, Staahltoft *et al.*(2023) developed an electrical virtual fence and GPS tracker to monitor and prevent the movement of bull calves in the Holistic Grazing System in the United Kingdom effectively. The system uses electrical impulses as warnings to force the cattle to remain within a predefined boundary. The electrical impulses can also be used to keep the cattle rustlers away from the virtual fence, making the system a potential tool for preventing cattle rustling in developing countries like Nigeria. However, the need for frequent maintenance, replacement and its high cost of about $300 have made the implementation of the system less feasible in developing countries like Nigeria due to most cattle farmers’ economic condition. Several challenges, such as inadequate battery life, the need for continuous maintenance, connectivity, and high cost, have negatively affected the widespread implementation of GPS cattle identification systems, especially in areas with limited infrastructural development (Francis et al., 2018). Similarly, the wide grazing areas and the unstable and harsh weather conditions have further affected the acceptance of the GPS technology in countries like Nigeria.

2.2.2 SIFT and SURF For Image Processing

Awad *et al.* (2013) integrated the Random Sample Consensus (RANSAC) algorithm for removing outliers with SIFT for feature extraction to pioneer the development of cattle identification using muzzle prints. The system achieved an impressive accuracy rate of 93.3% and addressed many challenges to provide a reliable and non-invasive method of cattle identification. Developing on this, Kumar *et al.* (2017) later integrated SIFT and SURF to investigate the unique patterns of muzzle print images to identify cattle biometrically. The system achieved an accuracy rate of 93.87% with the use of SIFT and SURF as texture feature descriptors on 500 cattle.

2.2.3 CNNs in Cattle Identification

Deep learning technique is another emerging technology that is advancing the field of biometric cattle identification systems through specializing in image processing. The ability of deep learning to process different biometric patterns such as facial features, muzzle prints, iris scans, and other distinct properties has made deep learning, particularly the Convolutional Neural Networks (CNNs), indispensable in modern livestock management. Building on this foundation, Shojaeipour *et al.* (2021) use a two-stage algorithm that combines YOLOv3 and ResNet-50 to develop an automatic mixed breed cattle identification system. This research study stands out for drastically reducing data requirements with the use of few-shot deep transfer learning and a SoftMax classifier that achieved an identification accuracy of 99.11%. Additionally, the limited challenges associated with datasets were overcome by the integration of data augmentation techniques that enhanced model performance resulting in benefitting deep learning (Wang & Deng, 2018). While SIFT and SURF have demonstrated effectiveness in extracting distinct visual features from muzzle prints, their application in real-world cattle management presents challenges. These include high computational costs, sensitivity to noise, and poor scalability in rural settings with limited infrastructure. Conversely, Convolutional Neural Networks (CNNs) offer a more scalable and automated approach by learning features directly from raw images, thereby reducing reliance on manual feature engineering. CNNs are also more adaptable to varying image qualities and lighting conditions, making them more suitable for deployment in field conditions. As such, CNNs are emerging as the preferred method for biometric cattle identification due to their superior performance, adaptability, and reduced need for preprocessing.

3. Methodology

3.1 Rationale for Muzzle Print Cattle Identification

There are things to consider when choosing a suitable biometric method as suggested by some researchers. For example, Corkery *et al.* (2007) suggest that a cattle identification method should be human-friendly, fraud-proof, easily obtainable, and cost-effective. Tharwat *et al.* (2014) echo the sentiments of Corkery *et al.* (2007) and further emphasize that the method should avoid invasiveness. Muzzle prints appear to fulfill all the conditions proposed by both researchers. Similarly, in most biometric methods of identification, processing time and accuracy pose major

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challenges. This makes the muzzle print method preferable due to its robustness and faster processing time (Awad et al., 2013).

3.2. ResNet-50 Architecture

ResNet-50 is the deep learning model that was used in this research to identify cattle based on their muzzle prints. ResNet (general term) was created by He et al. (2019) and introduced a clever approach called residual learning to help the network avoid the vanishing gradient problem often seen in very deep networks. This was done by allowing the network to skip layers through shortcut connections. ResNet models come in different depths such as ResNet-18, ResNet-34, and the ResNet-50 (Koonce, 2021). ResNet's architecture enables the training of extremely deep networks with improved accuracy, making it a great choice for tasks like recognizing cattle muzzle prints. Refer to Figure 6 for ResNet-50-based model architecture for cattle identification that illustrates the step-by-step processing from image acquisition to classification.

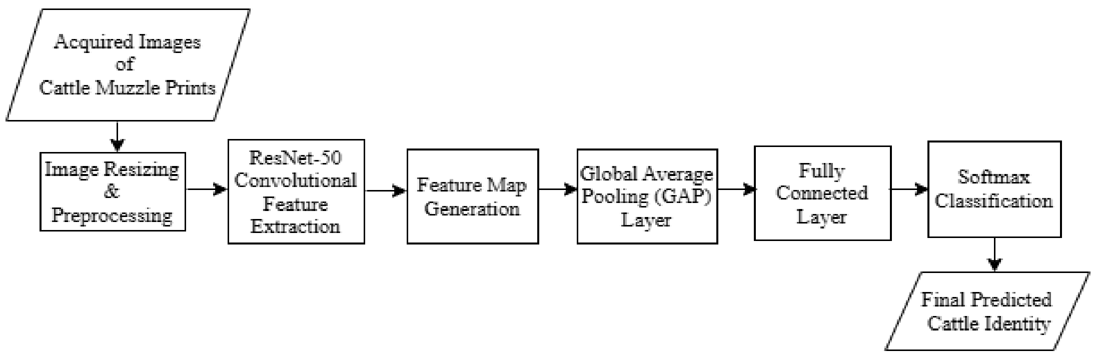

Figure 6: ResNet-50-based model architecture for cattle identification

3.3 Transfer Learning

The pre-trained ResNet-50 model was employed to leverage Transfer learning, significantly improving model convergence by reducing training time. Therefore, the ResNet-50 architecture was initialized with ImageNet pre-trained weights instead of training the network from scratch. This allowed the model to apply its earlier feature extraction experiences while adjusting to the targeted cattle identification task using muzzle print. Transfer learning ensured the model learned the muzzle print dataset patterns efficiently without overfitting. This was because the muzzle print dataset was extremely smaller compared to the ImageNet datasets that was used to pre-train the model. General features such as the edges, shapes and textures were captured by the pre-trained layers. The fine-tuning helped the model to adapt to unique cattle muzzle print patterns. Freezing the Lower Convolutional Layers and Fine-Tuning the Upper Layers are the two transfer learning implementation strategies. Refer to Table 1 for the differences between the original and modified ResNet-50 for cattle identification. Additionally, Refer to Figure 7 for Transfer Learning Process for ResNet-50 in Cattle Identification.

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Table 1: Differences between the original and modified ResNet-50

S/No	Feature	Original ResNet-50	Modified ResNet-50 for Cattle Identification
1	Pre-trained Dataset	ImageNet (general objects)	Muzzle print images from cattle
2	Final Classification Layer	1,000-class softmax layer	Custom dense layer for individual cattle
3	Trainable Layers	Mostly frozen (transfer learning)	Last 50 layers fine-tuned for feature adaptation
4	Feature Extraction	General object detection	Specialized in muzzle print biometric features
5	Regularization	Standard weight decay	Dropout & batch normalization added
6	Augmentation	General transformations	Muzzle print-specific transformations (flipping, zooming, etc.)
7	Optimizer	Standard SGD/Adam	Adam with fine-tuned learning rate

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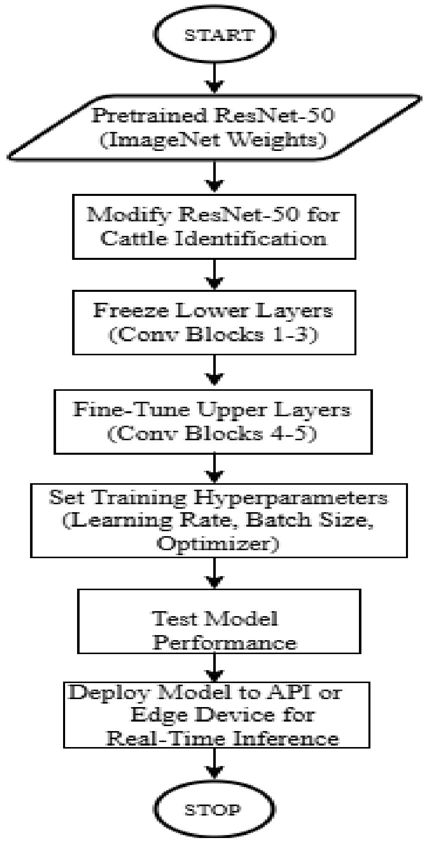

Figure 7: Transfer Learning Process

3.4 Stratified Sampling Approach

A stratified sampling approach was used during dataset splitting to maintain a balanced class distribution. This helped to ensure that each class of cattle was represented proportionally in all the three subsets to minimize class imbalance concerns that could bias the model towards certain cattle. Refer to Table 2 for Dataset splitting strategy used for training, validation, and testing and Figure 8 for Distribution of images across training, validation, and testing.

Table 2: Dataset splitting strategy used for training, validation, and testing

S/N	**Dataset Subset**	**Percentage (%)**	**Number of Images**	**Purpose**
1	Training Set	70%	727	Used to train the ResNet-50 model by updating weights and learning feature representations.

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2	Validation Set	20%	207	Used to fine-tune hyperparameters, prevent overfitting, and assess model performance during training
3	Testing Set	10%	104	Held out for final evaluation to measure the model's real-world accuracy

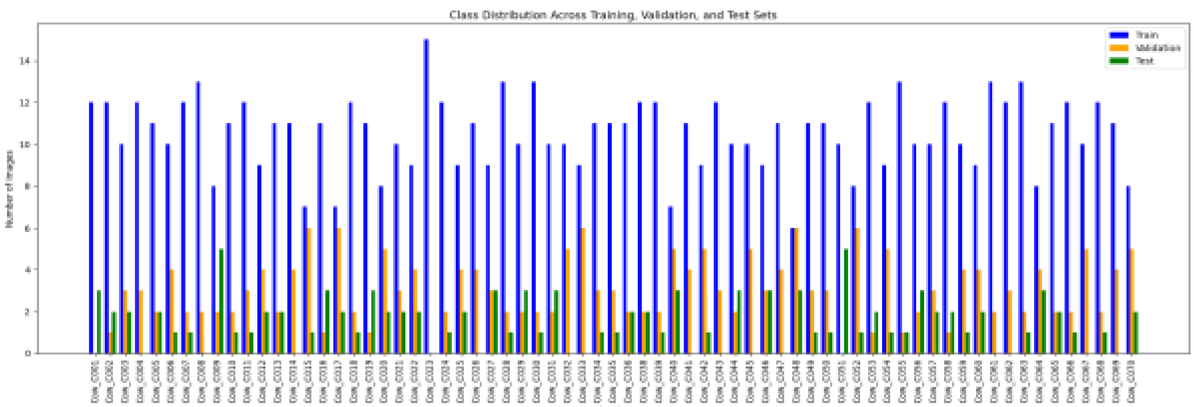

Figure 8: Distribution of images across training, validation, and testing

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4. Results and Discussion

The muzzle print images were used to train the ResNet-50 model with the goal of learning features that uniquely distinguish individual cattle. The proposed ResNet-50-predictive biometric identification model achieved a test accuracy of 97.60% in the end, with high prospect in recognizing individual cattle using their muzzle prints. The model showed consistent learning evolution in training epochs, accuracy of 6.1% in epoch 1 improved to greater than 99% in epoch 20. The validation accuracy followed the same trend, while the validation loss continually decreased, substantiating good generalizability as well as absence of overfitting. These parameters of performance are presented in Table 3, with the whole training log being presented in the Appendix in Table A for clarity and reproducibility. This outcome is in line with previous work such as that of Shojaeipour et al. (2021) and Islam et al. (2024) that achieved high accuracies with larger datasets using hybrid models. The high good performance achieved by this study despite limited dataset is a demonstrated the strength of the fine-tuned ResNet-50 model and the quality of preprocessing that was used. The preprocessing used included noise reduction, resizing, normalization, and augmentation. Additionally, L2 weight decay, early stopping, and dropout regularization techniques were involved to prevent overfitting and improve the models' robustness. Furthermore, the training and validation accuracy (Figure 9) and confusion matrix heatmap (Figure 10) indicates how the model did in terms of identifying the individual cattle out of the whole 70-class set. The prominent diagonal with nearly zero off-diagonal terms once again confirms that the model had high recall and precision, even for cattle that are physically similar in color, breed, or age.

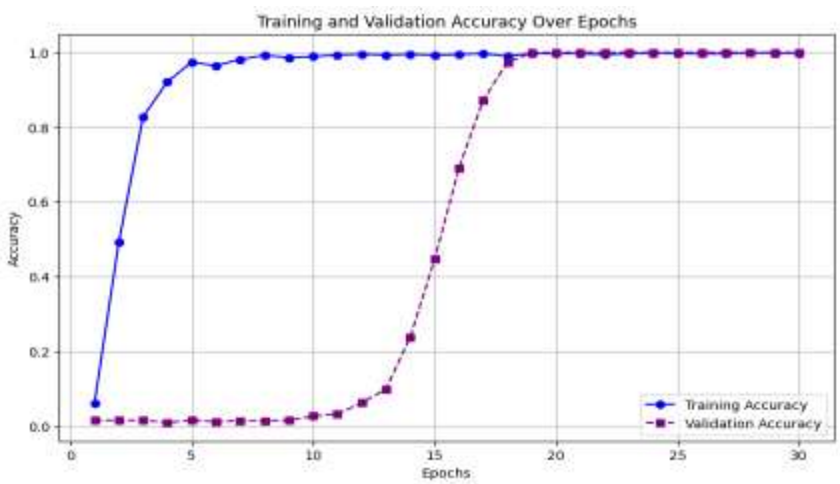

Figure 9: Training and Validation Accuracy over Epochs

Table 3: Validation and Test Set Performance Metrics

S/No.	Metric	Validation Set	Test Set
1	Total Images	207	104
2	Number of Classes	70	70
3	Accuracy (%)	100.00	97.60%
4	Loss	0.7861	0.7992
5	Precision	1.00	1.00
6	Recall	1.00	1.00
7	F1-Score	1.00	1.00

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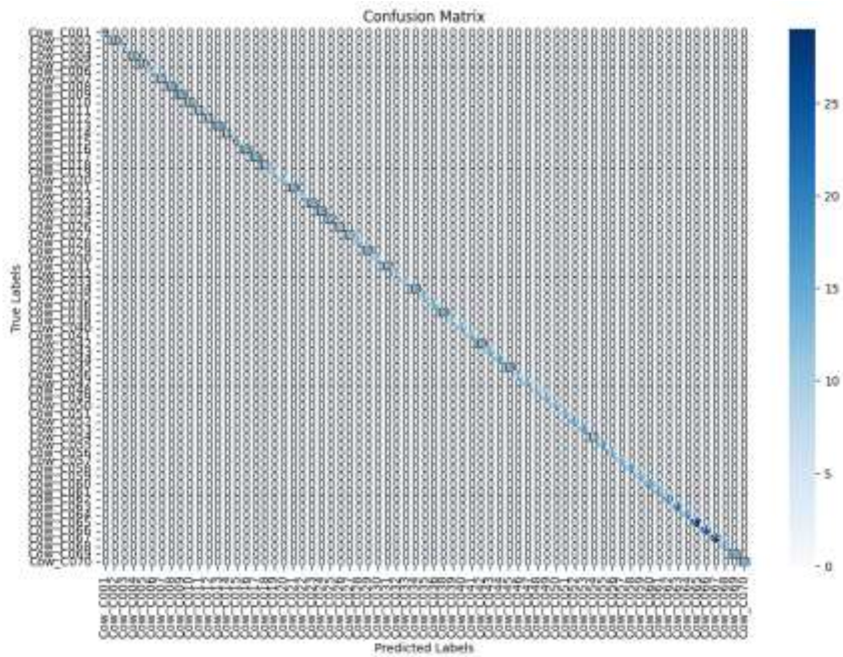

Figure10: Confusion Matrix

4.2 Limitations of Dataset Size and Environmental Variation

Despite achieving a high accuracy, the performance of this model is still limited by the small dataset size and the variability in the environment when the images are taken. The dataset consists of only 70 cows, hence may not cover sufficient variety as available in the real world, which could pose a threat of overfitting. Besides, variability in lighting, background and image angle may decrease the reliability of models in the field. To enhance the generalization, further studies could integrate the dataset of different scenes by standardizing the method of image acquisition.

5. Conclusion

The research proposal designed and validated a deep learning-driven cattle identification system using muzzle print biometrics, aimed at addressing the persistent problem of cattle rustling in Nigeria by providing a fraudproof cattle identification system. The system was developed from the ResNet-50 convolutional neural architecture and demonstrated strong potential for accurate identification of individual cattle through their inherent muzzle print uniqueness. With the cataloguing of muzzle images and extraction of feature vectors that are highly discriminative, the model was able to greatly surpass a major obstacle in cattle identification that has crippled the effectiveness of previous methods, the majority of them in the developing world. The research therefore offers a supplementary means to previous identification methods and contributes to the ultimate task of deterring cattle rustling.
Based on the findings, the study recommend the development of functional prototype that will integrate the biometric identification model with ownership demographic information for authentication. Research in multi-modal biometric systems could also make cattle identification more secure and robust in actual applications.

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Appendix

Table A: Training Progress and Performance Metrics Across Epochs

Epoch	Training Accuracy	Training Loss	Val Accuracy	Val Loss	Learning Rate
1	0.0610	6.4582	0.0152	6.0196	0.0001
2	0.4918	2.7630	0.0152	6.7284	0.0001
3	0.8275	1.4674	0.0152	7.8631	0.0001
4	0.9216	1.1056	0.0091	8.0900	0.0001
5	0.9739	0.9534	0.0152	8.0267	0.0001
6	0.9647	0.9320	0.0111	7.2764	0.0001
7	0.9812	0.9150	0.0141	7.0651	0.00002
8	0.9926	0.8546	0.0131	6.7601	0.00002
9	0.9862	0.8713	0.0152	6.3714	0.00002
10	0.9890	0.8597	0.0263	6.1701	0.00002
11	0.9931	0.8454	0.0323	5.9876	0.00002
12	0.9956	0.8447	0.0616	5.7180	0.00002
13	0.9929	0.8446	0.0990	5.2557	0.00002
14	0.9953	0.8385	0.2384	4.4114	0.00002
15	0.9926	0.8418	0.4465	3.2076	0.00002
16	0.9944	0.8297	0.6899	1.9977	0.00002
17	0.9972	0.8239	0.8727	1.2223	0.00002
18	0.9896	0.8417	0.9737	0.8803	0.00002
19	0.9971	0.8212	0.9990	0.8069	0.00002
20	0.9969	0.8213	1.0000	0.7992	0.00002
21	0.9972	0.8157	1.0000	0.7978	0.00002
22	0.9943	0.8232	1.0000	0.7967	0.00002
23	0.9968	0.8148	1.0000	0.7955	0.00002
24	0.9981	0.8107	1.0000	0.7943	0.00002
25	0.9975	0.8135	1.0000	0.7930	0.00002
26	0.9965	0.8115	1.0000	0.7918	0.00002
27	0.9963	0.8086	1.0000	0.7904	0.00002
28	0.9990	0.8013	1.0000	0.7890	0.00002
29	0.9978	0.8067	1.0000	0.7876	0.00002
30	0.9978	0.8040	1.0000	0.7861	0.00002