Non-Invasive Muzzle Matching for Cattle Identification using Deep Learning

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***Abstract*—Accurate cattle identification is an essential but complicated issue in the field of livestock management. Traditional identifying methods can involve invasive procedures, posing ethical difficulties and compromising animal welfare. This paper addresses this pressing issue by proposing a deep learning-based methodology for non-invasive cattle identification through muzzle matching. Our approach leverages a comprehensive dataset of 4923 cleaned and cropped muzzle images from 268 distinct cattle breeds. The model showcases exceptional performance with a training accuracy of 98.88% and a test accuracy of 100%. Importantly, our methodology avoids invasive procedures and exhibits adaptability, effectively handling introducing new animals into the system. This versatility ensures the model's reliability across diverse operational scenarios, making it a suitable candidate for insurance fraud prevention and animal trading applications. The paper also highlights critical future research directions, including expanding the dataset to encompass a broader range of cattle breeds and muzzle variations and the potential integration with other identification modalities.**

***Index Terms*—Cattle recognition, Muzzle point, Deep Learning, Non-invasive Techniques, Adaptability.**

I. Introduction

Identification and verification of animals are essential in a number of businesses, including insurance, animal trading, and agricultural management [1], [2]. In the past, methods like branding, ear tagging, and microchipping have been used to identify animals, but these approaches can cause stress to the animals, take a lot of time, and are prone to errors [3]–[6]. In recent years, non-invasive techniques, aided by advancements in machine learning and computer vision, have opened up new possibilities for accurate and efficient animal identification [7], [8].

The motivation for developing non-invasive muzzle matching arises from addressing challenges in insurance fraud and animal trading markets. In South Asian countries like India, instances of fraudulent insurance claims related to cow deaths have been reported, where individuals falsely claim that multiple cows have died to maximize their insurance benefits [9], [10]. Such fraudulent activities result in significant financial losses for insurers and undermine the integrity of insurance systems. Accurately identifying and verifying individual animals in animal trading markets can enhance traceability, prevent substitution, and ensure fair transactions.

This paper presents an innovative, non-intrusive technique known as "muzzle matching", which utilizes convolutional neural networks to analyze and compare the unique patterns present in cow muzzles. By harnessing the power of machine learning, we propose a deep neural network-based approach that offers significant advantages over invasive animal identification and verification methods. The methodology involves capturing high-quality images of cow muzzles, extracting the relevant information via deep learning algorithms, and conducting precise matching to ensure accurate results. This efficient system negates the need for invasive procedures and can potentially revolutionize fraud detection in insurance claims, enhance animal trading practices, and improve overall animal management systems.

The rest of the paper is structured as follows: Section II provides an overview of related animal identification work and the use of deep learning for similar tasks. Section III describes the methodology of muzzle matching using deep neural networks, including data collection, network architecture, training, and evaluation. Section IV presents experimental results and discussions on the performance of the proposed system. Finally, Section VI summarizes the paper and discusses future directions for research in non-invasive animal identification.

II. Related Works

Traditional invasive animal identification and verification techniques include branding [11], ear tagging [12], and microchipping [13]. Branding involves leaving a permanent mark on the animal's skin, generally with a heated metal item, whereas ear tagging is attaching tags to the animal's ear. Microchipping, on the other hand, requires implanting a small electrical chip beneath the animal's skin. These methods have gained widespread use because of their simplicity and inexpensive cost.

While invasive techniques have proven useful, they come with drawbacks and trade-offs. Branding and ear tagging can cause pain and discomfort to animals, potentially leading to stress and behavioral changes [4], [6]. Additionally, these methods may not be suitable for certain animals with sensitive skin or those involved in agricultural activities where the visibility of branding or tagging may impact their market value [1].

Although less invasive than branding or ear tagging, microchipping still requires a minor surgical procedure to implant the chip. This procedure carries inherent risks and requires specialized equipment and expertise. Moreover, microchips may migrate or become unreadable over time, making them less reliable for long-term animal identification and verification [8]. Invasive techniques also present challenges in scalability

TABLE I
CATTLE RECOGNITION ACCURACY VIA MUZZLE IMAGE MATCHING

Authors	Method/Model	Class size	Accuracy (%)
Noviyanto et al. [14]	SURF	8	90.6
Kumar et al. [15]	PCA + LDA	120	92.5
Hagar et al. [16]	Neural Net	28	92.76
Awad et al. [17]	SIFT + RANSAC	15	93.3
Mahmoud et al. [18]	SVM	52	96
Kumar et al. [19]	PCA + LDA + DCT	120	96.73

Principal Component Analysis (PCA), Linear Discriminative Analysis (LDA), Scale Invariant Feature Transform (SIFT), RANdom SAmple Consensus (RANSAC), Discrete Cosine Transform (DCT), Speed-Up Robust Features (SURF), Support Vector Machine (SVM)

and efficiency. The process of physically inspecting and reading individual tags or chips can be time-consuming, especially in large herds or during high-volume transactions. Additionally, errors may occur during manual data entry or tag/chip reading, leading to misidentification or data inconsistencies [12].

In response to the limitations of invasive animal identification techniques, a growing interest in non-invasive methods, such as muzzle image matching, has emerged [7], [8] that provide accurate and reliable animal identification and verification without subjecting animals to unnecessary discomfort or risks. While these methods have achieved significant accuracy on given datasets (Table I), their applicability in real-world scenarios remains a challenge, especially when confronted with unseen samples not included in their training data suggesting there is still room for improvement. It is well-documented that machine learning models perform optimally when test data closely aligns with the training data, and different machine learning algorithms can yield varied results for the same learning problem under identical settings [20]. As a result, these models may struggle with new cattle breeds, variable imaging conditions, or cattle muzzle changes due to age, health, or environmental factors. This underlines the necessity for continuous refinement and enhancement of these models for reliable application in diverse real-world scenarios.

Moreover, most of the current models have been tested on relatively small class sizes. The scalability of these models to larger herds, more diverse cattle populations, and broader geographical areas remains a significant concern. It is also essential to consider the computational efficiency of these models, especially in resource-constrained environments every day in agricultural settings.

Therefore, there is a compelling need to develop robust, adaptable, and scalable models for cattle recognition that are not only highly accurate on given samples but can also generalize effectively to new, unseen samples. Such models would provide a more reliable, efficient, and humane alternative to traditional invasive techniques, thereby advancing the field of livestock management and contributing to improved animal welfare and industry practices.

Fig. 1. A collection of six distinct muzzles used for muzzle detection training. These muzzles were carefully chosen to represent distinct patterns and variations observed in cow populations.

III. METHODOLOGY

A. Dataset

The dataset [21] contains muzzle/noseprint images of beef cattle collected explicitly for muzzle matching. The data collection process took place from March to July 2021 in the Midwest region of the United States. It comprises 4923 muzzle images of 268 cows collected using a mirrorless digital camera. The dataset encompasses three prevalent cattle breeds found in US feed yards: Angus, Angus x Hereford, and Continental x British cross. The dataset is a valuable resource for non-invasive muzzle-matching research, enabling the development and evaluation of machine learning algorithms for cattle identification and verification based on muzzle/noseprint images. Fig 1 showcases a diverse range of cow muzzles selected from the dataset.

B. Model Architecture

Our proposed model for muzzle matching builds upon the widely recognized VGGFace model [22], a pre-trained convolutional neural network renowned for distinguishing complex facial features and patterns. By leveraging the learned representations from this powerful model, we have designed an architecture tailored explicitly for identifying and validating cow muzzles, as illustrated in Fig 2.

To adapt the VGGFace model for muzzle matching, we added custom layers on top of the base model. The convolutional layers of the base model are frozen to keep the knowledge learned during pre-training and prevent overfitting. Adding such layers ensures that the network primarily focuses on learning the specific patterns and features in cow muzzles rather than re-learning general facial features. The custom layers consist of fully connected (dense) layers responsible for extracting and interpreting the learned representations from the base model. These layers enable the network to capture complicated relationships and patterns specific to cow muzzles. Dropout regularization is applied to prevent overfitting, and a softmax activation function is used in the final layer to predict the class probabilities of different muzzle identities.

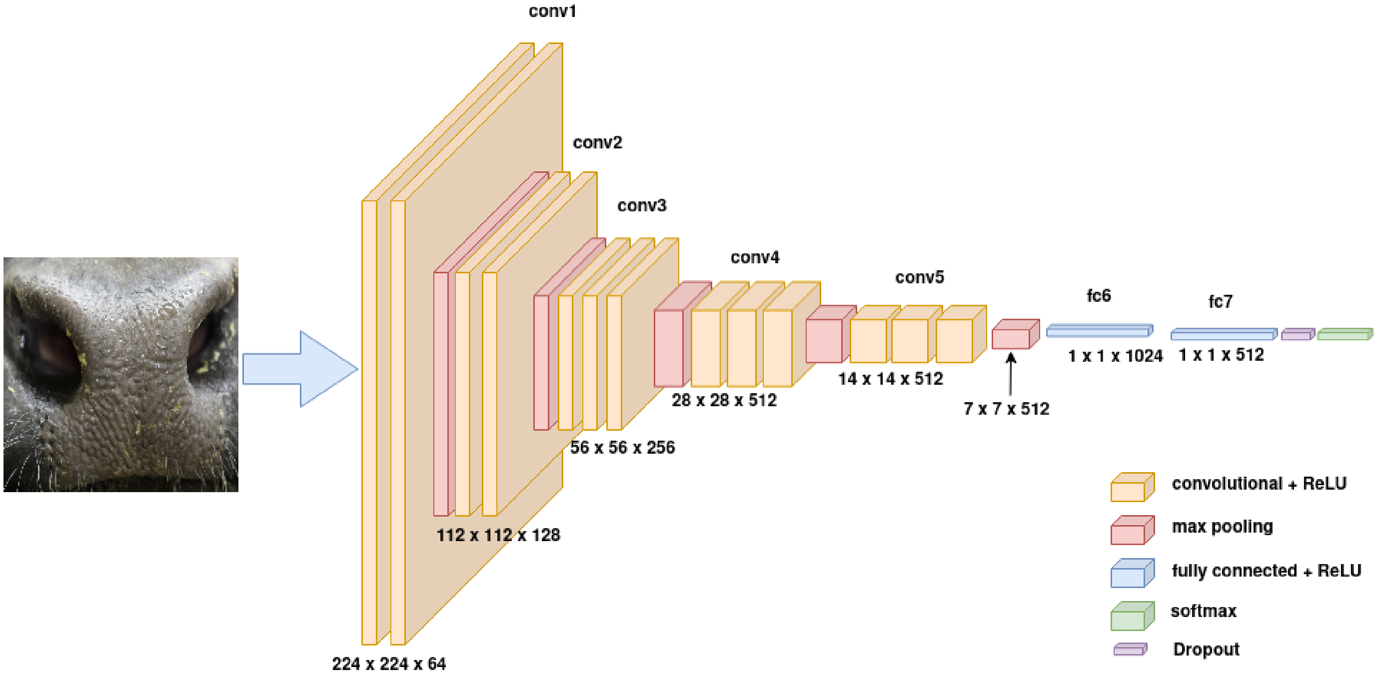

Fig. 2. Model Architecture of customed CNN model built upon VGGFace model

During training, a generator provides the model with batches of images, making the process effective and scalable. The Adam optimizer, which modifies the learning rate is used to enhance the model's performance. The model's performance during training is assessed using the accuracy metric and the categorical cross-entropy loss function. Two callbacks are utilized to prevent overfitting and monitor the model's training progress. The Early Stopping callback halts the training process if the loss does not improve after several epochs, preventing the model from continuing to train when it no longer benefits from additional iterations. The TensorBoard callback logs the training metrics, facilitating visualization and analysis of the model's performance using the TensorBoard tool.

The proposed approach provides a valuable foundation for training a deep neural network capable of non-invasive muzzle matching by combining the strengths of the pre-trained VGGFace model, custom dense layers, and appropriate callbacks.

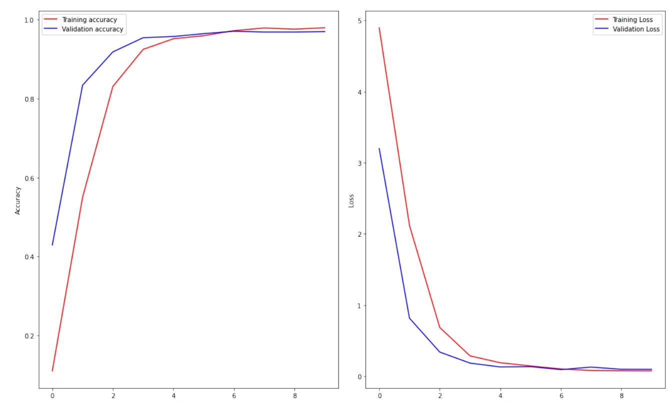

Fig. 3. Training and validation accuracy and loss with the initial dataset.

C. Model Training

The machine learning model was trained using TensorFlow, an open-source machine learning framework known for its versatility and efficiency. The training was conducted on a 16-inch Apple M1 Pro laptop, which has a 10-core CPU, 16-core GPU, 32 GB of LPDDR5 RAM, and a 512 GB SSD.

The model was trained over 10 epochs with a batch size of 256. Notably, the training process was completed in a remarkably short duration of 9 minutes and 33 seconds. This swift training time is indicative of the model's computational efficiency and the optimized hardware-software integration.

The rapid training time demonstrates the practicality of this model in real-world scenarios. This is particularly important in dynamic environments where models need to be updated or retrained frequently to adapt to new data or changing conditions. The ability to train quickly not only saves computational resources but also enables faster decision-making based on the model's outputs

The proposed deep learning model for non-invasive muzzle matching was trained and evaluated using the collected dataset of muzzle/noseprint images from cow cattle. The model demonstrated exceptional performance, showcasing its effectiveness in cattle identification tasks.

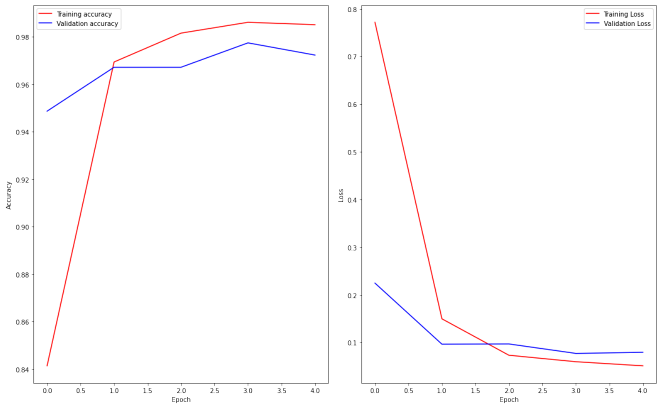

Fig. 4. Training and validation accuracy and loss after adding new classes.

IV. Results and Discussion

Our model achieved remarkable accuracy and robustness, accurately recognizing and matching muzzles across different individuals within the dataset. With a training accuracy of 98.88% and a test accuracy of 100%, the model showcased an improved ability to precisely identify and match cattle muzzles. One notable advantage of our model is its adaptability. When new animals were introduced to the dataset, the model could be easily retrained without compromising its performance. The training and validation accuracy and loss during the initial training phase are depicted in Fig. 3. Subsequent training, performed after adding new classes, shows corresponding accuracy and loss values presented in Fig. 4. By selectively retraining only the dense layers and freezing the convolutional layers, we avoided the need to train the entire model from scratch. This approach maintained the model's high performance and significantly reduced the computational burden of retraining on expanding datasets.

Our model's adaptability and ease of retraining are invaluable in practical scenarios where new cattle may be added to the population. It ensures accurate and reliable muzzle matching, even as the dataset evolves over time. This scalability and flexibility enhance the model's utility in cattle management and monitoring systems applications.

The excellent results obtained from the model highlight its potential in addressing challenges related to insurance fraud and animal trading, where accurate identification and verification of individual animals are crucial. The model provides a reliable solution without requiring invasive procedures by employing non-invasive techniques based on deep neural networks.

It is important to note that the model's success relies on the dataset's quality and representativeness. Including clean and cropped images covering multiple common cattle breeds enhances the model's ability to generalize and perform well on a diverse cattle range.

V. Future Work

The work presented in this paper lays a solid foundation for further research in the field of non-invasive cattle identification using deep learning-based muzzle matching. Future work can focus on expanding the diversity of the dataset, including a broader range of cattle breeds and variations in muzzle/noseprint patterns. This would facilitate a more robust model capable of handling various cattle breeds and diverse environmental conditions. Evaluating the model's performance in real-world scenarios will substantiate its practicality and reliability, providing valuable insights to further refine the model. Notably, considering potential adversarial attacks, as highlighted in recent research [23], should be integrated into future developments to ensure the model's robustness against such threats. Furthermore, the potential scalability of the model through distributed computing [24], [25] could enhance its performance and reduce training time, allowing for the handling of larger datasets and more complex cattle identification tasks. Finally, exploring the integration of other modalities, such as thermal imaging or 3D scanning, can provide additional pathways to improve the accuracy and robustness of cattle identification and verification systems.

VI. Conclusion

This paper presents a non-invasive method for cattle identification based on deep learning and muzzle matching. Our model stands out for its exceptional accuracy, offering a practical tool for various applications, including insurance fraud prevention and livestock trading. The model's versatility, as evidenced by the ease with which new animals may be introduced to the system, increases its potential for broader application.

Compared to previous methodologies, our model stands out as notably more accurate. As evidenced by the data in Table I, our model outperforms established methods in terms of accuracy. For instance, the SURF model by Noviyanto et al. [14] and the PCA + LDA + DCT model by Kumar et al. [19] only achieved accuracies of 90.6% and 96.73% respectively. However, our model achieved a training accuracy of 98.88% and a test accuracy of 100% across 268 classes. This performance demonstrates its capacity to recognize individual cattle and its flexibility with multiple breeds. The efficient training process, mainly when adding new classes, further enhances its versatility and scalability. This allows the model to rapidly adapt to new situations, hence expanding its potential uses. The model's non-invasive characteristics and adaptability make it a promising tool for numerous sectors and applications, marking a new tool for cattle identification systems.

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