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IMPROVED DEEP LEARNING MODEL FOR CATTLE IDENTIFICATION USING MUZZLE IMAGES

Using traditional methods such as ear tags, branding, and tattoos for cattle identification requires continuous human involvement and demands significant time and effort. Although radio-frequency identification (RFID) methods are widely used today, they also have certain disadvantages. The RFID devices used must be constantly installed, which can cause discomfort to the animals, and during their movements, the devices may become damaged or lost, leading to further issues. By using biometric features for cattle identification, these disadvantages are eliminated. In this method, animals are identified using their unique biometric features, such as iris patterns, skin textures, muzzle prints, and facial features. This article focuses specifically on identifying cattle based on their muzzle images. In this study, a total of 4923 images of 268 cattle were used. The architectures of eight different models were improved and selected for the training process, and the training was conducted. According to the results, the DenseNet-121, WideResNet-50, and Inception V3 models achieved the highest accuracy rates, with 99.2%, 99.1%, and 99.1%, respectively. These results demonstrate the effectiveness of the proposed architecture.

Key words: Cattle muzzle images, pattern recognition, feature extraction, biometric features, cattle identification, deep learning models, model architecture.

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Тұмсығы кескіндері пайдалану арқылы ірі қара малды сәйкестендіру үшін терең оқытудың жетілдірілген моделі

Ірі қара малды сәйкестендірудің дәстүрлі әдістерін, мысалы ретінде, құлақ сырғаларын, таңбалауды және татуировкаларды қолдану үнемі адамның араласуын, сондай-ақ уақыт пен күштің айтарлықтай шығынын талап етеді. Қазіргі уақытта радиожиілікті сәйкестендіру (RFID) әдістерінің кеңінен қолданылуына қарамастан, олардың да белгілі бір кемшіліктері бар. Бұл үшін қолданылатын RFID құрылғылар үнемі орнатылып тұруы қажет, бұл жануарларды мазасыздандыруы мүмкін, сонымен қатар олар қозғалған кезде құрылғылар зақымдалып немесе жоғалып кетуі мүмкін, бұл қосымша мәселелерге әкеледі. Ірі қара малды сәйкестендіруде биометриялық сипаттамаларды қолдану осы кемшіліктерді жояды. Бұл әдісте жануарлар олардың бірегей биометриялық сипаттамалары, мысалы, көздің радужка суреттері, тері текстурасы, мұрын іздері және бет ерекшеліктері бойынша анықталады. Бұл мақала ірі қара малды мұрын іздері негізінде сәйкестендіруге арналған. Бұл зерттеуде жалпы саны 4923 суреттен тұратын 268 ірі қара малдың бейнесі пайдаланылды. Сегіз түрлі модельдің архитектуралары жақсартылып, оқыту процесі үшін таңдалып, оқытылды. Зерттеу нәтижелері бойынша DenseNet-121, WideResNet-50 және Inception V3 модельдері ең жоғары дәлдікке, сәйкесінше 99,2%, 99,1% және 99,1% жетті. Бұл нәтижелер ұсынылған архитектураның тиімділігін көрсетеді.

Түйін сөздер: ірі қара малдың тұмсығы кескіндері, үлгіні тану, ерекшеліктерді алу, биометриялық белгілер, ірі қара малды сәйкестендіру, терең оқыту модельдері, модель архитектурасы.

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Улучшенная модель глубокого обучения для идентификации крупного рогатого скота с использованием изображений морды

Использование традиционных методов идентификации крупного рогатого скота, таких как ушные бирки, клеймение и татуировки, требует постоянного участия человека, а также значительных затрат времени и усилий. Несмотря на широкое применение радиочастотных методов идентификации (RFID) в наши дни, они также имеют определенные недостатки. RFID устройства, используемые для этого, должны постоянно устанавливаться, что может вызывать беспокойство у животных, и во время их передвижения устройства могут быть повреждены или потеряны, что приводит к дальнейшим проблемам. Использование биометрических характеристик для идентификации крупного рогатого скота устраняет эти недостатки. В этом методе животных идентифицируют по их уникальным биометрическим характеристикам, таким как рисунки радужки, текстуры кожи, отпечатки носа и черты лица. Данная статья посвящена идентификации крупного рогатого скота на основе отпечатков носа. В этом исследовании было использовано в общей сложности 4923 изображения 268 голов крупного рогатого скота. Архитектуры восьми различных моделей были улучшены и выбранных для процесса обучения и обучение было проведено. По результатам исследования модели DenseNet-121, WideResNet-50 и Inception V3 достигли наивысшей точности, составив 99,2%, 99,1% и 99,1% соответственно. Эти результаты демонстрируют эффективность предложенной архитектуры.
Ключевые слова: изображения морд крупного рогатого скота, распознавание образов, извлечение признаков, биометрические признаки, идентификация крупного рогатого скота, модели глубокого обучения, архитектура модели.

1 Introduction

Currently, artificial intelligence is one of the most important directions in modern technology and is widely applied in various fields. Artificial intelligence is aimed at implementing the capabilities of human intelligence through computers. Artificial Intelligence approaches human reasoning through a productive structure that encompasses data processing, calculation of algorithms, and machine learning among other things. Such a development enables extensive data to be examined and well-informed decisions to be rendered based on the information available. Another area of artificial intelligence that has attracted interest is classification which is the process of grouping information into categories or sets. It is an essential step in managing, analyzing and predicting of data. Classifying is applicable in a broad spectrum of industries such as health, finance, marketing and even livestock management. Extensive research has of late been done by scientists in these industries [1–4]. In the work of classification there is an objective of arranging the information according to set attributes. It involves the application of many methods and algorithms including deep learning models which are mostly machine-learning models. Object identification is also a part of this classification problem. In identification, each object is treated as a unique class. This article is focused on applying such an identification method to recognize cattle.

Cattle identification is one of the key aspects of effectively managing and monitoring the livestock industry. Cattle identification is the process of recognizing each individual cattle in a livestock farm. Currently, several methods are used for identification. These methods can be divided into contact-based and non-contact-based categories [5]. Contact-based methods include branding, freeze branding, ear tags, tattoos, and other techniques [6]. These identification methods always require human involvement, as well as time and effort. Additionally, these methods have their disadvantages. The procedures can be distressing for the animals, ear tags may be detached, and tattoos can deteriorate or become illegible over time. However, these methods are more cost-effective than others [7]. Another widely used contact-based method is the radio frequency identification (RFID) system [8]. This identification technique entails placing tag-based RFID with microchips on livestock ears. The radio frequency identification RFID tags have a unique code that can be picked by an appropriate reader enabling identification of livestock. Although this method seems to be expensive during initial installation within farms, it will be the most frequently used method within mechanized agriculture. Since all devices include chips that are believed to be unremovable, it has its demerits including bringing pain to the livestock, and chances of the chips being either lost or broken during movement [9]. Other non-contact methods use the animal's biometrics thus reducing the pain an animal goes through. Biometric features include iris images, skin patterns, muzzle images, and facial recognition [10].

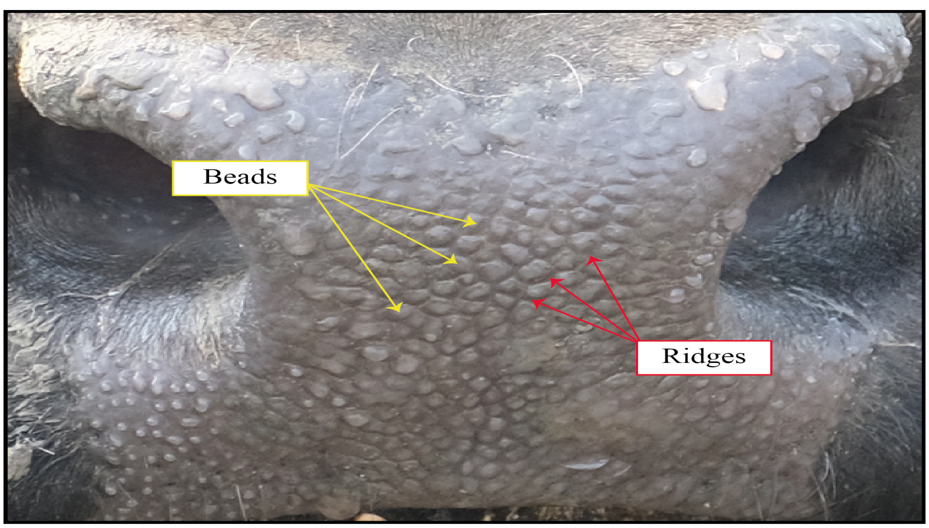

Figure 1: Biometric features in the muzzle image of cattle: The beads are marked in yellow, and the ridges are marked in red

Among the mentioned biometric features, identification using muzzle prints is a simple method, and interest in research in this area has been increasing recently [11–15]. The muzzle print of cattle contains unique features, much like human fingerprints [16]. There are two types of distinctive biometric features of the cattle's muzzle: beads and ridges (Figure 1). The beads have an uneven structure and resemble islands, while the ridges resemble rivers running between the islands. These beads and ridges serve as unique biometric identifiers for recognizing cattle. Research has confirmed that muzzle prints are accurate and remain unchanged over time, making them a reliable biometric identifier. This identifier has been studied since 1921 [17].

The aim of this study is to collect muzzle images of cattle, create a dataset, and apply various deep learning methods to identify the cattle based on the dataset. The results will be analyzed using metrics such as image processing speed, training speed, and accuracy levels.

2 Materials and Methods

2.1 Image Collection

In order to form a dataset of cattle muzzle images, images from previous studies [6] were used. The dataset contains 4,923 images of 268 cattle [18]. All images are high-resolution, RGB color images, taken with a digital camera equipped with a 70–300 mm F4-5.6 focus lens. The muzzle sections were cropped from the cattle images in the dataset (Figure 2).

Figure 2: Samples of images from the dataset consisting of cattle muzzle prints

It is important to note that the color and texture of cattle muzzle prints may appear very similar, but when analyzing the beads and ridges, significant differences become noticeable. The images in the dataset vary in size, and they need to be standardized before being fed into the training model. Based on the analysis of previous research and experimental results, the image size was set to 300 x 300. It was found that training at this size operates faster. While reducing the image size to 250 x 250 accelerates training speed, it may lead to the loss of finer features. However, the 300 x 300 resolution was retained for this study, as it facilitates faster processing while preserving more detailed information crucial for cattle identification based on muzzle print characteristics.

In this work, the applied image augmentation techniques such as shifting, rotating, color manipulation and blurring images, which all helped to increase the number of sample images, were used in order to obtain better model accuracy. Also, as a result of carrying out data augmentation, the accuracy of the model is expected to be improved in the future due to various repetitions of the existing images.

2.2 Deep Learning Models

After conducting a comprehensive review of global research on the subject, eight deep-learning models were chosen for image classification tasks. The selected models include AlexNet, GoogleNet, DenseNet, WideResNet, MobileNet V2, MobileNet V3, ShuffleNet V2, and Inception V3. Table 1 provides a detailed summary of these models along with their key characteristics.

Table 1: Characteristics of deep learning models used in the study

No.	Model name	Number of parameters (million)	Model size (MB)
1	Alexnet	62	233
2	GoogleNet	13	50
3	DenseNet-121	8	30
4	WideResNet-50-2	69	262
5	MobileNet V2	3.5	13
6	MobileNet V3 Large	5.5	21
7	ShuffleNet V2	2.2	8.6
8	Inception V3	27	103.67

2.3 Training Process

With the assistance of transfer learning, the models have been implemented using the Pytorch framework. This approach involved utilizing models pre-trained on the ImageNet dataset [19]. The model's fully connected layer was modified to tailor it for the classification of the current dataset. The convolutional network weights remained pre-trained, while the final layer was fine-tuned specifically for cattle identification tasks. This strategy enhances training efficiency. Proper selection of hyperparameters and configurations helps achieve high accuracy levels. Based on the acquired results, the subsequent parameters and configurations were determined: the training process is set to a maximum of 50 epochs, utilizing the Adam optimization algorithm, and employing the Cross-Entropy loss function. The optimizer's peak learning rate is established at 1e-4, with a gradient clipping threshold of 0.1 implemented to mitigate potential gradient explosion. Additionally, a regularization coefficient of 0 was applied to minimize overfitting risks. Early stopping is incorporated, halting the training process after 7 epochs in the absence of any improvement in the accuracy metric.

Throughout the training phase, accuracy, loss, and additional metrics were evaluated at each epoch. The progression of accuracy throughout training is illustrated in Figure 3. The duration of each training epoch, as well as the overall training time, was meticulously documented. Based on the outcomes obtained from the experiment, the hyperparameters' optimal values were determined.

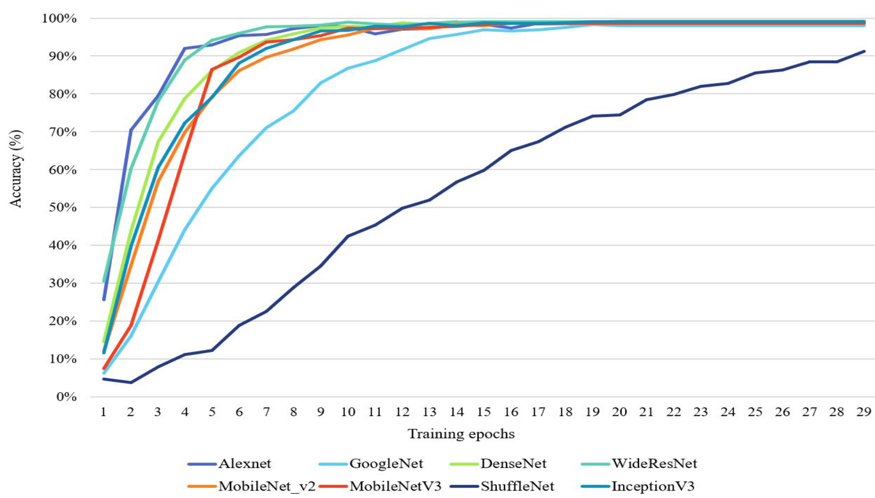

Figure 3: The Accuracy of deep learning models

The dataset comprises 268 distinct objects, each represented by 4 to 70 images. Objects with fewer images introduce challenges in object recognition, primarily due to class imbalance. To resolve this challenge two approaches were implemented, the Weighted Cross-Entropy (WCE) loss function [20] and data augmentation techniques [21]. Augmentation techniques aimed at increasing the dataset size and diversity. These strategies were applied across all models and enabled the determination of optimal accuracy and computational efficiency. Among these metrics, accuracy was prioritized as the most critical factor.

The WCE loss function assigns greater weights to cattle classes with a smaller number of images. This weighting is calculated using the following approach:

$$WCE_{\text{loss}} = -\sum_{i=1}^{C} w_i t_i \log(p_i) \tag{1}$$

where $p_i \in \mathbb{R}^{268}$ refers to the probabilities assigned to each of the 268 cattle classes in the output of the LogSoftMax layer. C represent the total number of cattle, while t_i indicates the actual probability for the cattle, which is calculated as follows:

$$t_i = \begin{cases} 1, & \text{if } i = \text{true} \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

w_i – the individual weight assigned to the i-th cattle is calculated as follows:

$$w_i = \left(\frac{N_{\max}}{N_i} \right) \tag{3}$$

N_i denotes number of images for the i-th cattle, N_max denotes number of images devoted to one cattle in the dataset (which in this dataset equals 70).

70% of the dataset was used for training and the remaining 30% for testing. The image channel pixel color intensities were rescaled to the interval [0,1], which increases the effectiveness of image recognition, as noted by [22].

The model training was conducted on a computing machine with the following specifications: Intel i7-11800H 2.3GHz – 4.6GHz, 32 GB DDR4 RAM, RTX 3070 8 GB GDDR6.

During the training process, modifications were made to the architecture of the selected models. Instead of using the original fully connected output layer, a new architecture was developed. In the new architecture, the number of outputs in the last layer matches the number of classes in the dataset, i.e., 268 outputs. A linear layer was added to the output part of the initially trained model. This layer had an input size of *inputs* from the previous model and an output size of 512 for the next layer. The number of neurons in this linear layer was determined to be optimal for our case based on the results of the experiments, with 512 neurons selected. Between this linear layer and the final output layer, a ReLU activation function and a dropout layer were added to prevent overfitting. The final layer is a linear layer, and the architecture concludes with the LogSoftMax function. The proposed architecture is illustrated in Figure 4c.

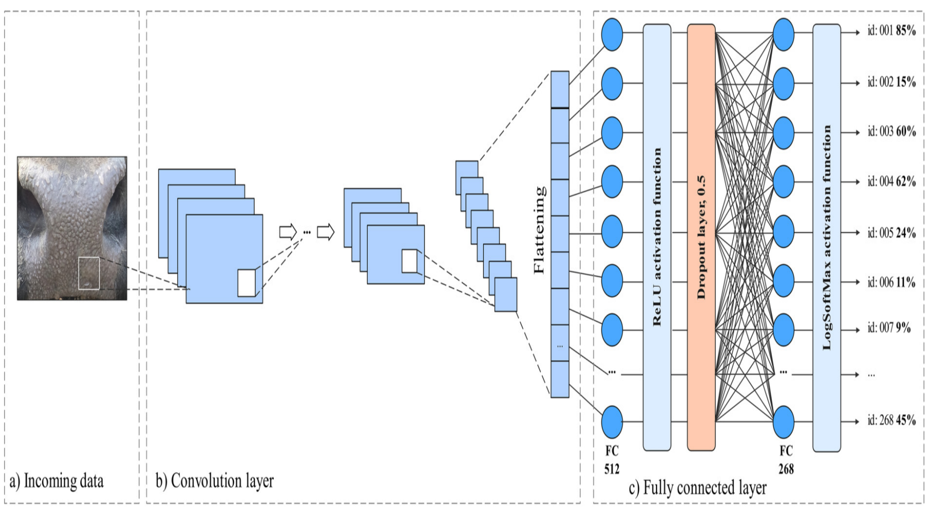

Figure 4: General architecture of the training model: (a) input data, (b) convolutional layers of each model, (c) improved fully connected linear layer

3 Results

Eight optimized models were trained using the previously described settings, hyperparameters, and architecture. A maximum of 50 training epochs was set, but early stopping was applied if accuracy did not change over a period of time. Consequently, high accuracy was achieved between epochs 13 and 29. There was an average of 33 to 67 minutes spent on each model training process. Table 2 presents the training results for the models. Model accuracy ranged from 91% to 99% according to the results. DenseNet-121 is the model with the highest accuracy, while GoogleNet has the lowest accuracy.

This study achieved high performance with enhanced models. The DenseNet-121 model achieved 99.2% accuracy, while the WideResNet-50 and Inception V3 models achieved 99.1%

accuracy. This result can be compared with other studies focused on identifying cattle based on the muzzle image [6, 15, 23, 24]. The improved model comparison Muzzle image cattle identification was performed in [6] and our enhanced model demonstrated better performance. Comparison results are shown in Table 2.

Table 2: Training results of the models and comparison with other studies

No.	Model name	Epochs	Accuracy (%)	Training Time (minutes)	Comparison with other studies [6]
1	Alexnet	19	98.8	34	96.5
2	GoogleNet	20	97.9	39	59.4
3	DenseNet-121	20	99.2	67	93.0
4	WideResNet-50	15	99.1	38	89.6
5	MobileNet V2	16	98.6	34	-
6	MobileNet V3 Large	18	98.5	33	95.9
7	ShuffleNet V2	29	91.2	51	1.2
8	Inception V3	19	99.1	41	81.7

4 Conclusion

The study established the usefulness of the pre-trained models regarding cattle identification. Using a large dataset with pre-trained models not only improves model performance in terms of accuracy but also cuts down training time massively. The process of identification was done from muzzle images and eight previously known models were chosen as the subject of testing. The Modifying changes done to the final output layer of the models resulted in the proposal of an alternative structure. The new structure outperformed previous training standards for models with DenseNet-121, WideResNet-50 and Inception V3 reporting accuracy rates of about 99.2%, 99.1% and 99.1% respectively. These results support the effectiveness of the new architecture. Even when there are differences in the types of cattle, the conditions of data collection and the architectures of the different models, all the experiments reached an accuracy rate of about 90% confirming the effectiveness of the proposed method.

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