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Individual Buffalo Identification Through Muzzle Dermatoglyphics Images using Deep Learning Approaches

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ABSTRACT

Animal identification is essential for routine farm operations, residue traceback, insurance, and ownership management. Owing to their uniqueness, incorrigible nature, tamperproof over time, environment-friendly, and pain-free, visual biometrics-based animal identification has recently gained momentum over traditional animal identification methods. Among visual biometrics-based cues, muzzle identification is a simple and relatively low-cost method. Therefore, to address the inherent significant limitations of conventional animal identification systems, we undertook this investigation to collect a database of digital images of muzzles that works as a benchmark, to apply deep learning frameworks to identify individual buffaloes from their muzzle images, and to compare their accuracy in terms of their identification capabilities. Muzzle images of 198 Surti buffaloes were subjected to transfer learning and fine-tuning processes in deep-learning neural networks. The performance was recorded for each pre-train model (ResNet50, InceptionV3, VGG16, AlexNet) with different hyperparameters of the epoch, batch size, and learning rate. A perusal of the data revealed that ResNet50 has the highest train accuracy (99.8%) and test accuracy (99.69%) among all four models used. AlexNet has the lowest train accuracy (90.8%) among the models. The findings concluded that all these four models could be applied to identify individual buffaloes; however, ResNet50 had the highest accuracy, and deep learning applications have great potential for individual buffalo identification and are promising tools for precision livestock farming.

Keywords:
Animal identification; buffalo; convolutional neural network; muzzle dermatoglyphics; transfer learning

1. Introduction

Animals need to be identified for various purposes like maintenance of proper records on the farm, accomplishing feeding, breeding, milking, healthcare practices properly, establishing parentage, registration of offspring, registration of pure-bred animals, disease, and residue trace

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back, insurance, and to prove ownership when animals are theft or lost. An ideal identification method should be accurate, permanent, visible, and readable from a distance, widely acceptable, cheaper, easy to acquire, fraud-proof, and humane [1, 2]. Traditional animal identification methods could be broadly classified into mechanical, electronic, or biometric methods. These animal identification systems include ear tags, tattooing, freeze branding, hot iron branding, neck chains, ear notching, electronic identification, radio frequency identification (RFID), and muzzle ink printing [3, 4]. However, these systems are invasive, prone to be lost or damaged, labor-intensive, require handling and restraining of animals, comparatively not cost-effective, and sometimes not good enough for traceability purposes [5-7]. Further, electronic identification devices incur relatively higher costs, are susceptible to being hacked or physically exchanged between animals for fraudulent practices, and are prone to loss of transponder [8]. Therefore, a robust and efficient bovine identification technique is the need of the hour.

Owing to their uniqueness, incorrigible nature, tamperproof over time, environment friendly, and pain-free, the visual biometrics-based animal identification (viz. coat pattern, iris scanning, retinal imaging, muzzle, and facial recognition, DNA pairing) has gained momentum recently [3, 9-12]. Among these biometrics-based animal identification, muzzle identification is a simple and relatively low-cost method [13].

Animal nose or bovine muzzle was considered a unique biological identifier, such as human palms, as bovine muzzle consists of the distribution of valleys and ridges over it [14]. Hence, Animals can be identified by their muzzle prints [15-24]. The muzzle pattern could be captured either by lifting the muzzle pattern on paper or taking photographs of the muzzle. The paper ink technique has the following drawbacks- it is an inconvenient, time-consuming process, a particular skill is required to control the animal, prints lack quality, and cannot be stored and used in a computerized manner [25, 26]. The advent of powerful microcomputers and advanced programming languages has made it possible to resolve the shortcomings of these traditional methods of identifying animals based on their muzzle pattern using digital image processing techniques. Therefore, driven by this need, we undertook this investigation to collect a database of digital images of muzzles that works as a benchmark, to apply deep learning frameworks to identify individual buffaloes from their muzzle images, and to compare their accuracy in terms of their identification capabilities.

2. Related Work

Many prior research reports on animal biometrics for their identification are available for wildlife and livestock. Computer-assisted individual animal classification relied on various distinct patterns and markings of the animals. viz. coat pattern analysis [27-29], facial recognition [7, 11] and muzzle print pattern analysis [18, 30, 31].

Since 1921, animal muzzle or nose print has been investigated as a distinguished biomarker [15]. Recently, many researchers have evaluated various computer vision frameworks for identifying cattle and buffalo from their muzzle images. These models have utilized different approaches viz. deep learning [31, 32], fuzzy-k-nearest neighbor [18], decision trees [33], AdaBoost classifier [34], support vector machine [6, 22], bag-of-visual words [35] and SIFT matching [36] to identify individual cattle. Noviyanto and Arymurthy [36] proposed a beef cattle identification system based on muzzle patterns using the Scale Invariant Feature Transform (SIFT) algorithm with an Equal Error Rate (EER) value of 0.0167. Awad *et al.,* [23] reported a robust and fast cattle identification scheme based on muzzle print images using local invariant features, which could resolve some of the shortcomings of the traditional identification methods regarding accuracy and processing time. They coupled the Random Sample Consensus (RANSAC) algorithm with the Scale Invariant Feature Transform (SIFT) in their proposed scheme. They achieved 93.3% accuracy in reasonable processing time compared to 90% identification accuracy achieved by other traditional identification schemes.

Subsequently, Hadad *et al.,* [14] evaluated two different bovine classification models using an Artificial Neural Network (ANN) and a K-nearest neighbor Classifier (KNN). He concluded that the experimental result evaluation proves the advancement of the KNN model over ANN as it achieves 100% classification accuracy in case of an increase in the number of classification groups to twenty-five compared to 92.76% classification accuracy achieved from the ANN classification model. Sharma *et al.,* [37] reported a framework based on transfer learning in a Convolutional Neural Network (CNN) to construct an automated wild animal identification system. The proposed framework achieved an accuracy of 96 % on the test dataset. Bello *et al.,* [8] proposed a stacked denoising auto-encoder and deep belief network for recognizing and identifying an individual cow using a cow nose image pattern. They studied 4000 cow nose images from an existing database of 400 individual cows and concluded that the deep belief network outshines other methods with approximately 98.99% accuracy.

Ketmaneechairat *et al.,* [26] classified 765 muzzle print images of Kamphaeng Saen beef cattle using Scale Invariant Feature Transform (SIFT) for detecting the interesting points and Random Sample Consensus (RANSAC) algorithm and achieved 92.25 percent accuracy. Li *et al.,* [13] evaluated various deep-learning image classification models for recognizing 268 feedlot finishing cattle. He reported 98.7 % accuracy for identification. These reported works concluded that the muzzle images could be a biomarker for individual bovine identification and are favorable for precision livestock management. Lee *et al.,* [32] used 9230 muzzle images from 336 Hanwoo cattle to classify them using a deep-learning model. They performed transfer learning with the tiny, small, and medium versions of Efficientnet v2 models with SGD, RMSProp, Adam, and Lion optimizers. They reported that the small version using Lion showed the best validation accuracy of 0.981 in 36 epochs within 12 transfer-learned models. Further, the small version using Adam showed the best test accuracy of 0.970, but the small version using RMSProp showed the lowest repeated error.

3. Methodology

In this study, we leveraged the potent techniques of transfer learning and fine-tuning to elevate the performance and effectiveness of neural networks in tackling the intricacies of muzzle classification. Our exploration delves into the innovative synergy between these two techniques, presenting a comprehensive approach to address the shortcomings of traditional animal identification methods.

3.1 Experimental Data

Digital images of the muzzle of 198 Surti buffaloes were recorded using a Nikon D5600 camera (effective pixels:24 megapixels, sensor size: APS-C (23.5 x 15.6 mm), sensor type: CMOS, ISO: Auto, 100 -25600, max resolution: 6000 x 4000, color space sRGB, white balance presets: 12) under similar environmental condition and camera setup. A uniform distance of 0.5 m was maintained between the muzzle and camera lens for all animals. The sample of muzzle images of the dataset is depicted in Figure 1. These Surti buffaloes were maintained at the Livestock Research Station under Navsari Agricultural University, Navsari, Gujarat, India. All experimental animals were maintained under a loose housing system and subjected to standard routine management practices. The classification of experimental buffaloes according to their age groups is depicted in Table 1.

Fig. 1. Sample of muzzle images of the dataset with 198 classes

Table 1
Classification of experimental buffaloes according to their age groups

Sr. no.	Age group	Number
1.	0-1 year	59
2.	More than 1-3 years	48
3.	More than three years	91
Total		198

The obtained muzzle images were subjected to transfer learning and fine-tuning processes in deep learning neural networks to propose a buffalo classification system at the Faculty of Computer Science and Information Technology, University Putra Malaysia, Malaysia. The performance was recorded for each pre-train model with different hyperparameters of the epoch, batch size, and learning rate. The images were preprocessed prior to the deep neural network learning processes.

We used a split-folders application to divide 4,628 muzzle images into train, test, and validation sets using a ratio of 60:20:20, respectively. The 198 individual animals under the study have been referred to as classes for the image analysis.

This study's dataset comprised diverse-resolution images and was stored in the JPG (Joint Photographic and Experts Group) file format. The images exhibited variations in their pixel dimensions, with some having higher resolutions than others. This diversity in resolutions and file formats was representative of real-world scenarios and added a degree of complexity to the image preprocessing process. The images were stored in a structured directory format, with one subdirectory for each class or category of images. Within each subdirectory, the images were stored as individual files. This organization simplified data loading for training and validation.

3.2 Image Pre-Processing

Each of these datasets underwent the same preprocessing method to provide consistency across the dataset, resulting in the model producing more accurate and consistent results. The pixels consist of RGB values that are of type integer and are in the range of 0 to 255. Then, it is converted into floats and scaled to lie in the range of 0 to 1 as machine learning optimizers are tuned to work well with small numbers. Then, the images were randomly zoomed with a factor up to 0.1 because the original images were already centered and focused on the muzzle. At the same time, a slight zoom introduces a form of scale invariance. These images were translated by randomly shifting the width and height dimension by 0.2 to enhance the model's ability to identify the object from different perspectives. The choice to employ only zoom and translate transformations for data augmentation is to ensure that the core features of interest, such as the muzzle, remained prominent and unaltered while still introducing a subtle degree of variability to enrich the dataset without compromising the integrity of the central object of analysis.

3.3 Model Architecture

Our proposed model for muzzle identification builds upon the four pre-trained convolution neural networks renowned for distinguishing complex features and patterns, including Inception V3 [38], ResNet50 [39], VGG16 [40], and AlexNet [41], to harness the complementary strengths of these architectures. Our framework of the buffalo recognition system is depicted in Figure 2. By leveraging the diverse capabilities of each model, our approach aims to enhance accuracy, robustness, and generalization across a wide range of muzzle images, thereby improving the overall performance of the identification system.

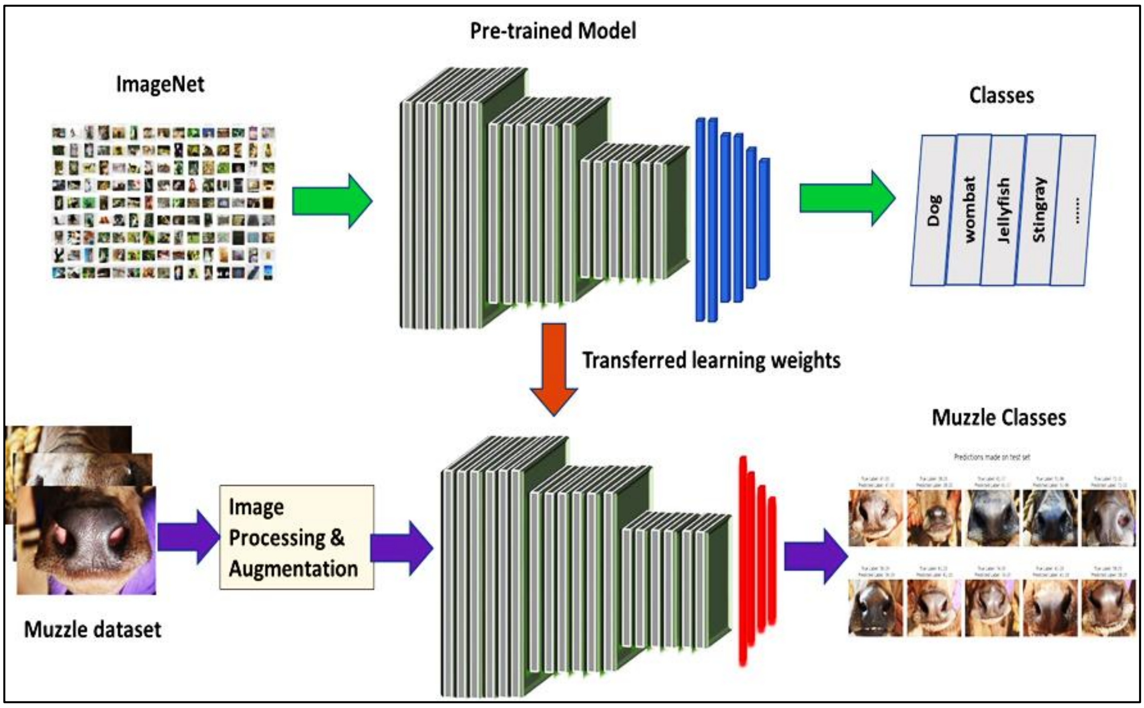

Fig. 2. Framework of the buffalo recognition system

Prior to model training, all images were standardized to a common resolution of 100x100 pixels and contained color information in three channels (RGB) as required by the pre-trained models, using an image resizing procedure. This procedure allowed for uniformity in input dimensions, enabling consistent and fair evaluations across the dataset despite initial image resolution and format disparities.

Depending on the model architectures, we added different custom layers on top of the base model to adapt the four models for muzzle identification. 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 buffalo muzzles rather than re-learning general vast ImageNet features. Meanwhile, AlexNet was uniquely trained on a dataset comprising 87,000 RGB images of healthy and diseased crop leaves, categorized into 38 distinct classes [41].

The custom layers for VGG16 consist of a flattened layer to transform the multi-dimensional output from the convolutional layers into a one-dimensional vector. This flattening layer was essential to prepare the data for subsequent fully connected layers. Then, a fully connected layer with 512 units and ReLU activation was added to capture complex patterns and higher-level features in the flattened representations. The number of units in this layer can be adjusted based on the complexity of the problem. Then, to mitigate overfitting, a dropout layer with a dropout rate of 0.5 was introduced immediately after the first fully connected layer. Dropout randomly deactivates neurons during training, promoting model generalization. The final fully connected layer consists of 198 units, corresponding to the number of classes in our specific task. It employs a softmax activation function to produce class probabilities, enabling multiclass classification.

The custom layers for ResNet-50 are closely related to customized VGG16 layers, with the primary distinction being the introduction of a BatchNormalization layer in ResNet-50 immediately after the last convolutional block and just before the fully connected layers. This means that after the activations from the Dense layer are computed, BatchNorm normalizes these activations before they are passed to the subsequent Dropout layer and final Dense layer for classification.

Meanwhile, the custom layers for Inception V3 consist of a global average pooling layer to average values across all spatial locations to reduce the spatial dimensions of the feature maps while retaining the most important muzzle features. It also helps in reducing overfitting and improving generalization. Then, the fully connected layer consists of 198 units, corresponding to the number of classes in our specific task. It employs a softmax activation function to produce class probabilities, enabling multiclass classification.

The custom layers for the AlexNet model involved transferring pre-trained weights from a previously trained AlexNet model and fine-tuning it for the current task. Initially, the model loads a pre-trained AlexNet model containing weights learned from 87,000 RGB images of healthy and diseased crop leaves. These weights were stored in an HDF5 format named "AlexNetModel.hdf5." The model performs an iterative process that simultaneously goes through the pre-trained AlexNet model and custom AlexNet models' layers. During the iteration, the model checks if the target layer (from the custom AlexNet model) and the source layer (from the pre-trained AlexNet model) have weights. If both layers have weights, the weights from the pre-trained model are copied to the corresponding layers in the custom model. This step was crucial as it initializes the custom AlexNet model with knowledge gained from the pre-trained model, which may have learned useful features from a different dataset.

During training, a generator provides the models with batches of images, as shown in Table 2, making the process effective and scalable. The Adam optimizer modifies the learning rate and enhances 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 proposed approach provides a valuable foundation for training a deep neural network capable of muzzle buffalo identification by combining the strengths of the pre-trained VGG16, ResNet50, InceptionV3, and AlexNet models, custom dense layers, and appropriate callbacks.

Table 2
Batch size and number of epochs for each model

Hyperparameters	Pre-trained model			
	ResNet50	InceptionV3	VGG16	AlexNet
Batch Size	12	64	64	64
Epoch	70	70	60	150

3. Results

The machine learning models were trained using TensorFlow, an open-source machine learning framework known for its versatility and efficiency. The trainings were conducted on a six-core AMD Ryzen 54600H processor and the NVIDIA GeForce GTX 1650Ti 4GB GDDR6 GPU.

The results, shown in Figures 3, 4, 5, and 6 reveal the best loss and accuracy on the training and validation datasets when training on all four pre-trained models. Each of the figures has three plots. The first plot presents the training and evaluation metrics that offer insights into the model's performance and convergence throughout the training process. The second plot delves into the dynamics of the learning rate and its role in guiding the optimization process during training. Lastly, it visually represents the model's predictive capability and generalization, offering a closer look at its accuracy and loss trends over multiple epochs.

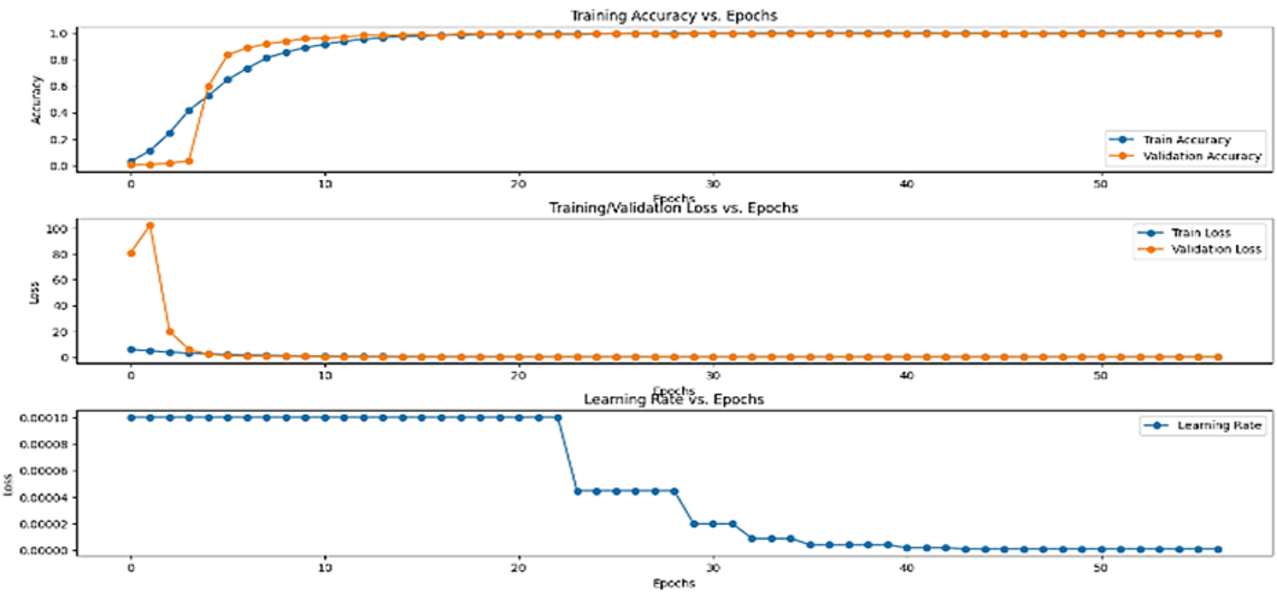

Fig. 3. ResNet50: Learning curve graphs explaining training accuracy and loss (blue) and validation set accuracy and loss (orange)

The ResNet50 curve shows that the training begins with a very high loss and low accuracy, indicating that the model's initial predictions are inaccurate. The model also achieves impressive performance in later epochs. The training loss is significantly reduced, and the validation accuracy reaches high values (e.g., 0.9953 and 0.9965). This indicates that the model is likely converging and can generalize well to unseen data, as indicated by the high validation accuracy.

Meanwhile, the learning curve for InceptionV3 shows that the training started with a high loss (5.3051) and low accuracy (0.0115), as well as validation loss (5.3636) and validation accuracy (0.0059). As the training progresses, the loss decreases, and the accuracy increases for both training and validation datasets. After the first epoch, the training loss drops to 5.1630, and the training accuracy increases to 0.0219. The validation loss also decreases to 5.1200, and the validation accuracy increases to 0.0220. This trend continues over subsequent epochs, with training and validation metrics improving gradually. In the end, after 70 epochs, the training loss becomes 0.1558, and the training accuracy reaches 0.9815. The validation loss becomes 0.2820, and the validation accuracy reaches 0.9492.

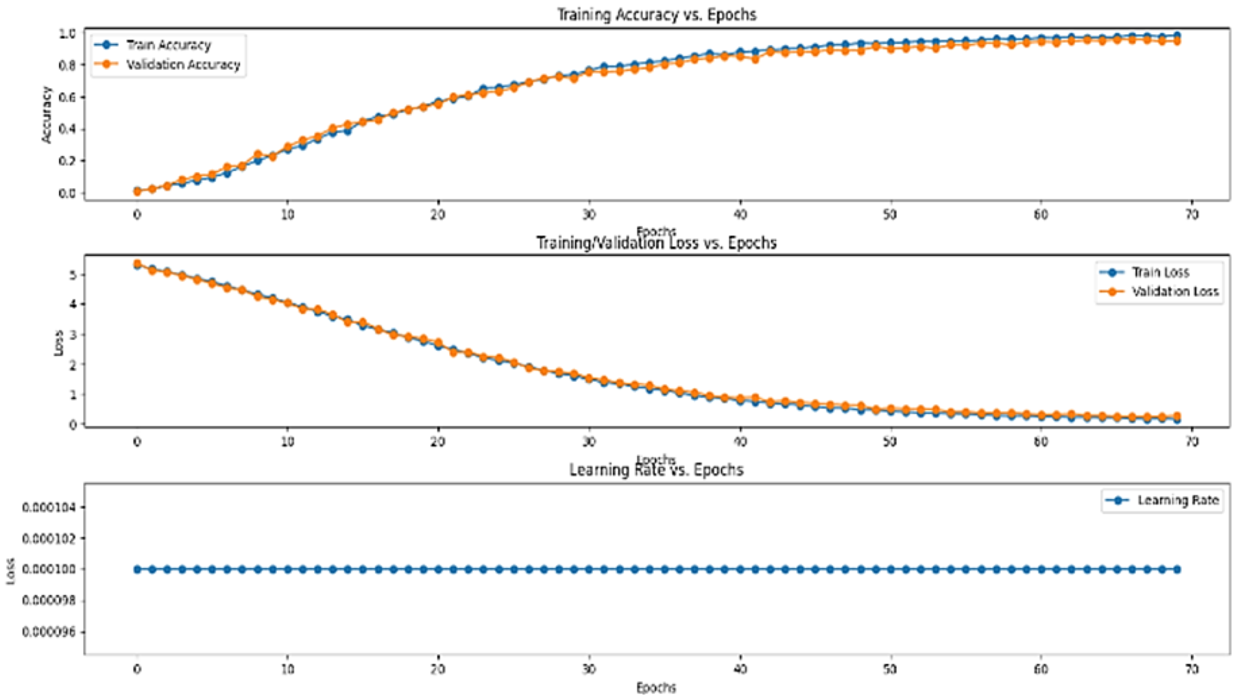

Fig. 4. InceptionV3: Learning curve graphs explaining training accuracy and loss (blue) and validation set accuracy and loss (orange)

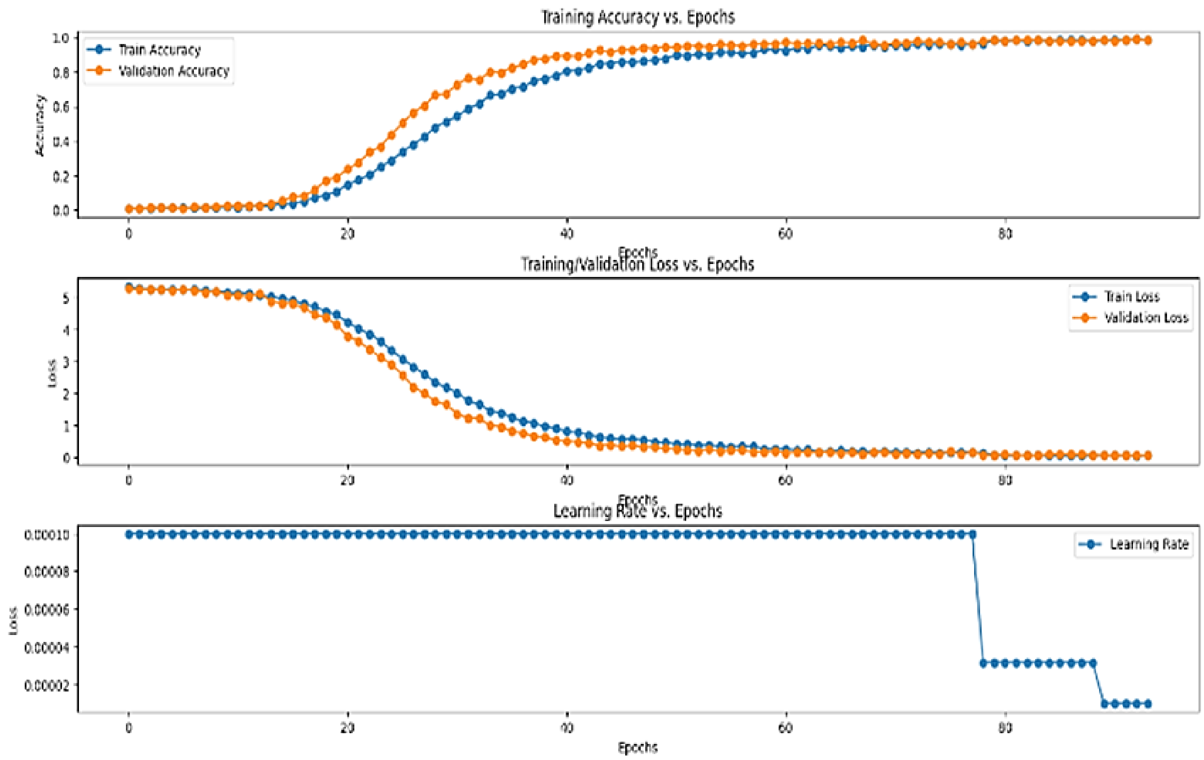

Fig. 5. VGG16: Learning curve graphs explaining training accuracy and loss (blue) and validation set accuracy and loss (orange)

At the beginning of training (epochs 1 to 10) of VGG16, the model's training and validation losses are relatively high, and the training and validation accuracies are low. This indicates that the model still needs to perform better on both the training and validation data, and there is room for improvement. As training progresses (epochs 11 to 60), the training and validation loss decreases, and the training and validation accuracies increase. This shows that the model is learning from the training data, and its performance on training and validation data is improving. In the middle of training (epochs 61 to 90), the learning rate is reduced (lr: 1.0000e-04 to 3.1623e-05), a common technique to fine-tune the model and avoid overshooting the optimal weights. This leads to a further reduction in training and validation loss and an improvement in training and validation accuracies. Towards the end of training (epochs 91 to 150), the model's performance continues to improve, but at a slower pace. The learning curve converges, indicating that the model is close to optimal performance on the given task.

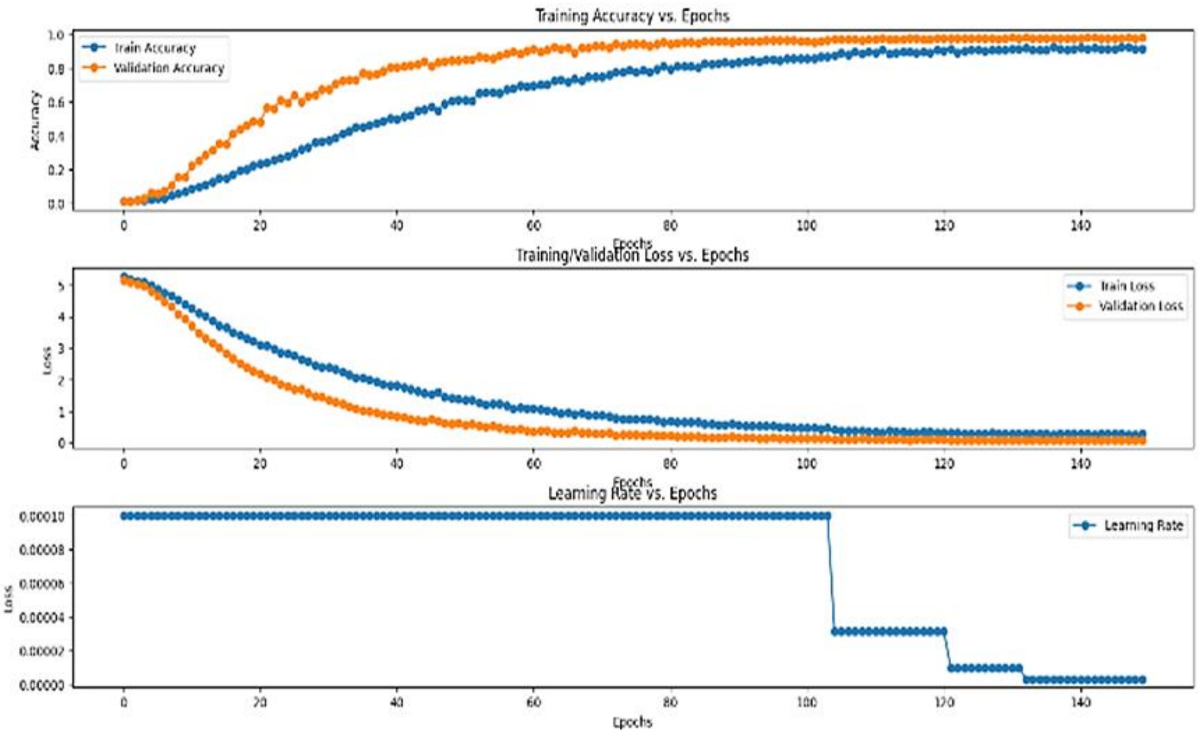

Fig. 6. AlexNet: Learning curve graphs explaining training accuracy and loss (blue) and validation set accuracy and loss (orange).

The training process for AlexNet starts with high loss values (around 5) and low validation accuracy (around 1.4%) in the first few epochs. This is normal in the beginning when the model is learning random weights. As the training continues, the loss decreases gradually, indicating that the model is improving. Simultaneously, the validation accuracy increases, so the model is better at generalizing to new data. The training time per epoch seems relatively high (ranging from around1100 seconds to almost 2000 seconds). This might be due to various factors, such as the model architecture's complexity and the dataset's size. After around 50 epochs, the model performs significantly better, with a validation accuracy of about 85%, and keeps improving further. Some validation accuracy and loss fluctuations might be observed across epochs, but the general trend is toward improvement. The final few epochs show that the model converges well, with high validation accuracy and relatively low loss.

Table 3 shows the proposed deep learning models for buffalo muzzle identification for the trained and evaluated using the collected datasets. The model demonstrated exceptional performance, showcasing its effectiveness in buffalo identification tasks. Therefore, ResNet50 is the best-performing model in this comparison. It achieves high accuracy and low loss on the training and validation datasets, indicating strong generalization capabilities. However, depending on the application's specific requirements, other models like VGG16 and AlexNet might still be reasonable choices, given their good validation accuracy and lower parameter counts.

Table 3
Observation of metrics of pre-trained models

Metrics	Pre-trained models			
	ResNet50	InceptionV3	VGG16	AlexNet
Train accuracy	0.9984	0.9774	0.938	0.9088
Validation accuracy	0.9969	0.9500	0.9752	0.9772
Train loss	0.0229	0.1669	0.2163	0.2846
Validation loss	0.0182	0.2620	0.1142	0.0842
Total parameters	24,740,422	22,208,486	17,176,070	25,538,118

Based on the test results of the four models of ResNet50, VGG16, InceptionV3, and AlexNet, as shown in Table 4, several observations can be made. Firstly, all models exhibit strong performance across various metrics, including precision, recall, and F1-score, indicating their ability to classify instances across different classes accurately. Specifically, ResNet50 and InceptionV3 demonstrate the highest overall accuracy of 99%, closely followed by VGG16 and AlexNet, with 91% and 93% accuracy, respectively. Additionally, ResNet50 and InceptionV3 consistently achieve high precision, recall, and F1 scores across most classes, showcasing their robustness in capturing both positive and negative instances. On the other hand, VGG16 and AlexNet, while slightly lower in accuracy, still maintain respectable performance levels, particularly in terms of precision and recall. Overall, these results highlight the effectiveness of all four models in accurately classifying instances, with ResNet50 and InceptionV3 standing out as particularly strong performers.

Table 4
Classification report of pre-trained models of the test set

Class	Precision	Recall	F1-score	Support
ResNet50				
01-17	0.83	1.00	0.91	5
01-18	1.00	1.00	1.00	7
01-19	1.00	1.00	1.00	5
:	:	:	:	:
82-17	1.00	1.00	1.00	6
83-17	1.00	1.00	1.00	6
84-17	1.00	1.00	1.00	9
Accuracy			0.99	1082
Macro average	0.98	0.98	0.98	1082
Weighted average	0.99	0.99	0.99	1082
VGG16				
01-17	0.83	1.00	0.91	5
01-18	0.86	0.86	0.86	7
01-19	1.00	0.80	0.89	5
:	:	:	:	:
82-17	0.86	1.00	0.92	6
83-17	1.00	1.00	1.00	6
84-17	1.00	1.00	1.00	9
Accuracy			0.91	1082
Macro average	0.89	0.86	0.86	1082
Weighted average	0.92	0.91	0.90	1082
InceptionV3				
01-17	0.83	1.00	0.91	5
01-18	1.00	1.00	1.00	7
01-19	0.62	1.00	0.77	5

Table 4. Continued
Classification report of pre-trained models of the test set

Class	Precision	Recall	F1-score	Support
:	:	:	:	:
82-17	1.00	1.00	1.00	6
83-17	0.67	1.00	0.8	6
84-17	1.00	1.00	1.00	9
Accuracy			0.93	1082
Macro average	0.91	0.90	0.89	1082
Weighted average	0.93	0.93	0.92	1082
AlexNet				
01-17	0.83	1.00	0.91	5
01-18	0.86	0.86	0.86	7
01-19	1.00	0.80	0.89	5
:	:	:	:	:
82-17	0.86	1.00	0.92	6
83-17	1.00	1.00	1.00	6
84-17	1.00	1.00	1.00	9
Accuracy			0.91	1082
Macro average	0.89	0.86	0.86	1082
Weighted average	0.92	0.91	0.90	1082

Figure 7 represents an example of wrong predictions made on the test set for the ResNet50 model. The perusal of age group data revealed that the buffaloes which were wrongly classified by the model were comparatively at a younger stage (less than three years of age) and were still growing. Pandey [42], Mishra *et al.,* [43], and Singh and Patel [44] reported that the muzzle pattern changes till the animals reach maturity. Therefore, the wrong prediction made by the model may be due to partially established muzzle dermatoglyphs.

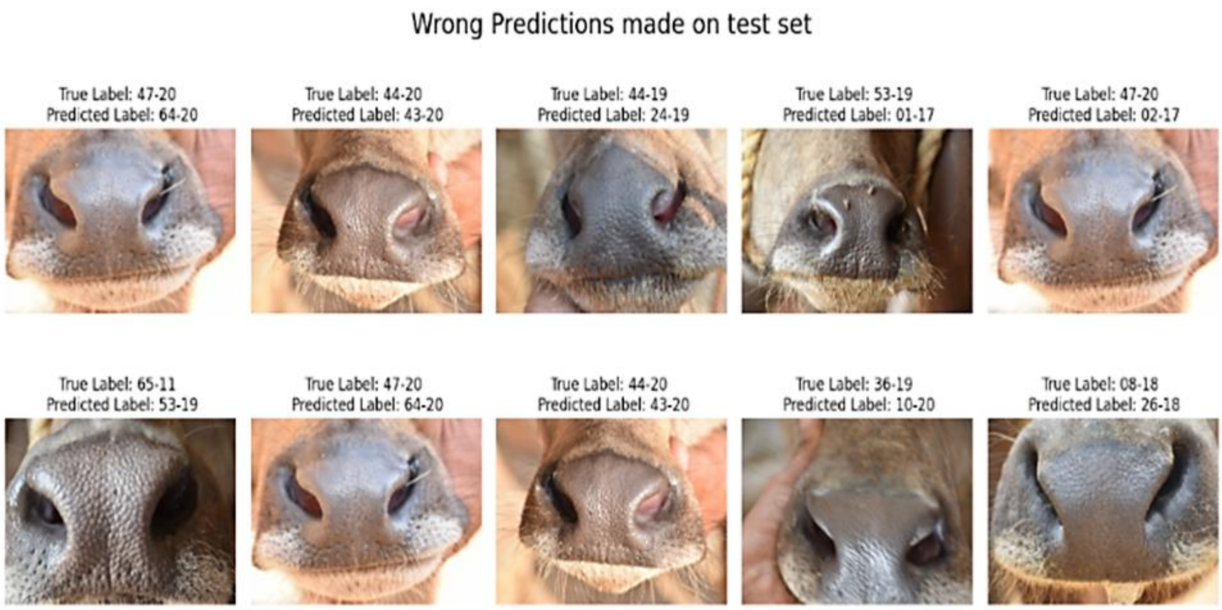

Fig. 7. Wrong prediction on the test set by the ResNet50 model

4. Conclusions

To conclude, pre-trained models hold a significant advantage over a simple CNN, and in this study, the knowledge transfer from the source domain (ImageNet) to the target domain (muzzle images) produced high accuracies of up to 99.89%, and F1 scores up to 98%. This work can be extended to include different datasets. Further, as per accessible reports, there is no real-time buffalo recognition system based on muzzle images in vogue. Hence, these neural network models may act as a tool to offer the necessary solutions for ownership management to reduce false insurance claims, traceability, and other routine farm management practices under farm and field conditions.

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