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Computer Vision for Emotion Identification on Sheep Images

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Abstract. The rising global demand for meat and dairy products has accelerated the expansion of livestock farming, underscoring the need for advanced technologies to ensure animal welfare and productivity. This research explores the potential of automated monitoring systems, leveraging depth sensors and time-of-flight cameras, to provide valuable insights into environmental conditions, nutrition, health, and productivity. These systems enable the early detection of abnormal behaviors in large-scale farming operations, paving the way for more effective management practices. The study emphasizes the importance of understanding animal needs and introduces advanced models, including EfficientNet, ResNet50, ResNet101, ResNet152, and VGG16, for emotion recognition in sheep. These models achieve impressive accuracy rates ranging from 88% to 93%, significantly enhancing the ability to detect and classify emotional states such as pain. This capability represents a vital component of precision livestock farming, a practice that integrates real-time data with machine learning to support informed decision-making, optimize yields, and mitigate risks. Furthermore, the research highlights methodologies for animal identification, body condition assessment, and pain estimation, showcasing the potential of sophisticated imaging and perception technologies to revolutionize livestock farming. By improving welfare and operational efficiency, these advancements offer a sustainable approach to addressing the growing challenges in modern agriculture.

Keywords: Computer vision. EfficientNet. Emotion detection. Pre-trained model. ResNet101. ResNet152. ResNet50. VGG16. YOLOv8.

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1 Introduction

Due to increasing demand for meat and dairy products to support a growing population, livestock farming has expanded worldwide, raising concerns about animal welfare and health and emphasizing the need to understand animal requirements to establish new production standards. Despite the challenges, monitoring farm animals' behavior using advanced technologies such as automated monitoring with depth sensors and time-of-flight cameras (BAMJI et al., 2022; STRAW, 2021) provides valuable insights into environmental conditions, nutrition, health, and productivity.

Furthermore, current social and ethical issues emphasize the need for better agricultural practices and welfare for farm animals, focusing on pain and animal well-being. Guidelines for managing pain in cattle, horses, sheep, and pigs include evaluating, treating, analyzing the cost-effectiveness of pain relief, and using pain scoring systems to improve animal welfare through improved farming methods and relevant laws and regulations (STEAGALL et al., 2021; PESSANHA et al., 2023). Recognizing the emotions of farm animals can allow farmers and field technicians to monitor their stress levels, detect early-stage diseases, and optimize care routines, leading to significant improvements in animal welfare.

A decision support system integrating real-time data and expert knowledge with machine learning and statistical analysis could help farmers recognize problems with the livestock and make informed decisions, increasing product yield and the management of risks (NILOOFAR et al., 2021; ROY et al., 2022). In this context, there is a great need for systems capable of automatically recognizing the emotional state of farm animals.

Recent research has significantly advanced the recognition of human emotions through facial, speech and sentiment analysis (XU et al., 2024). However, there is very little research on emotion recognition in farm animals. This is an urgent need that this research aims to tackle.

In this paper, we examined the use of the Deep Learning models ResNet50, ResNet101, ResNet152, VGG16, EfficientNet, and YOLOv8 to classify whether a sheep is in pain based on its image. The classification scores of each model are evaluated in terms of precision, recall and F1-score. The results presented here are expected to be an important reference for researchers working in this field, contributing to build knowledge around suitable models for the assessment of the health status of farm animals.

1.1 Contributions of the Research

- **Novelty:** This research introduces the novel application of advanced pre-trained models (EfficientNet, ResNet variants, and VGG16) specifically tailored for detecting emotional states in sheep.
- **Necessity:** There is a critical need for automated, non-invasive systems capable of recognizing the emotional state of farm animals; identifying stress or pain early allows farmers to optimize care routines, mitigate risks, and significantly improve animal welfare.
- **Impact:** The study demonstrates that deeper neural networks are highly capable of extracting nuanced facial features, successfully distinguishing between sheep in pain and those without. These advanced models achieved superior performance with accuracies ranging from 88% to 93% and precision rates up to 93%, outperforming simpler architectures like YOLOv8.

2 Literature Review

Emerging standards focus on understanding animal needs, particularly by monitoring pig and cattle behaviors to improve their well-being and productivity. Using machine vision technologies such as 3D imaging systems and 2D cameras enables automated monitoring to track livestock behaviors in large-scale farms, helping to detect abnormalities early on (NASIRAHMADI; EDWARDS; STURM, 2017; REZA et al., 2024; ARULMOZHI et al., 2021; YU et al., 2024). Researchers have also explored the use of precision livestock technologies such as biometric sensors, big data, and blockchain in the digitalization of livestock farming. Biometric sensors monitor each animal's health and behavior in real-time for population-level analysis (NEETHIRAJAN; KEMP, 2021; SARWAR et al., 2021).

Recent research has successfully applied deep Learning (DL) and IoT technologies for physical monitoring. For instance, studies have used biometric sensors and extreme gradient boosting to classify cattle activities such as rumination and grazing with high accuracy (DUTTA et al., 2022). In sheep specifically, computer vision has been utilized for non-invasive weight prediction (SANT'ANA et al., 2021) and aerial detection using custom Convolutional Neural Networks (CNNs) (SARWAR et al., 2021). However, these methodologies are often domain-specific; a model designed for weight estimation or activity tracking through neck-mounted sensors lacks the architectural nuance required to interpret subtle facial micro-expressions associated with pain.

Current literature on animal emotions is heavily weighted toward pigs and cattle. Notable advancements include the use of Coordinate Attention mechanisms and specialized loss functions in models like CReToNeXt-YOLOv5 to improve pig face emotion detection (NIE et al., 2024). Despite these improvements, existing studies face glaring constraints regarding scalability and dataset limitations, as many models are trained on specific, balanced datasets that fail to represent the environmental variability of large-scale farming, and techniques involving 3D imaging or complex template matching for body part segmentation often require high computational resources, hindering their deployment on smaller, resource-limited operations (JIA et al., 2021).

Traditional approaches for animal emotion detection relied on handcrafted features and segmentation, which, while computationally inexpensive, failed in scenarios requiring the analysis of nuanced facial changes, such as sheep ear positions and eye shapes. Modern deep learning architectures (ResNet, VGG16, EfficientNet) have shown promise in identifying these subtle indicators of the Sheep Pain Facial Expression Scale (SPFES).

As summarized in Table 1, while existing works achieve high accuracy in specialized tasks like body condition scoring (LIU; HE; NORTON, 2020) or heat stress monitoring (TSAI et al., 2020) , they rarely address the generalizability of pain detection across diverse sheep populations. This study addresses this gap by evaluating deep learning models' ability to extract these high-level features from sheep-specific facial datasets, providing a scalable, non-invasive alternative to traditional pain scoring systems.

3 Methods

The following steps are involved in emotion detection on farm animals through computer vision, as illustrated in Figure 1.

1. Images acquisition
2. Label the images with corresponding emotions
3. Cleaning, normalization, and augmentation of images
4. Model selection
5. Model training
6. Model evaluation
7. Deployment of the model
8. Classification of emotions in new images

The dataset used in this study is the Sheep Facial Expression Primary Dataset (NOOR; ZHAO, 2020), which is publicly available on Mendeley Data. This dataset consists of 1,500+ high-resolution sheep face images collected from multiple sources including ImageNet, NADIS, Pixabay, Flickr, and Getty Images (NOOR et al., 2020). The images are divided into two subsets: normal (no pain) and abnormal (with pain) sheep faces. Examples are presented in Figure 2, 3.

The abnormality assessment is based on the Sheep Pain Facial Expression Scale (SPFES), which evaluates facial features including ear position (pinna visibility), eye shape (V-shape vs. U-shape), and mouth characteristics (MCLENNAN et al., 2016). Images with clearly visible ear pinna indicate no pain, while less visible or non-visible pinna suggests low to high pain levels, respectively. Similarly, eye and mouth configurations following V-shape patterns indicate normal states, while U-shape patterns suggest pain (HÄGER et al., 2017).

While the original dataset contains over 1,500 images, a highly curated and perfectly balanced subset of 280 images was selected for this study to ensure the highest quality feature extraction. The dataset was divided as follows: approximately 70% for training (200 images), 15% for validation (40 images), and 15% for testing (40 images; 20 per class). All images were resized to 200 × 200 × 3 pixels to maintain consistency across the training process.

Based on this dataset, we trained and evaluated the performance of state-of-the-art Deep Learning models in recognizing sheep in pain. The following DL models were assessed in terms of precision, recall, and F1-score: EfficientNet, ResNet (variants 50, 101, and 152), VGG16, and YOLOv8. The pre-trained classification models (EfficientNet, ResNet variants, and VGG16) were all trained for 25 epochs. YOLOv8, primarily known as an object detection model, was included in this study as a comparative baseline to demonstrate if its localized feature extraction capabilities could offer any advantage over traditional CNNs in binary emotion classification tasks.

In this work, we used the Tensor Flow framework with Keras API on Google Colab to perform image processing, feature extraction, and classification. Data augmentation was performed using a program written in Python 3.6 with OpenCV library. All models were trained, validated and tested on Google Colab with T4GPU, except the YOLOv8 classifier. The YOLOv8 emotion detector was built, trained, and deployed on the Roboflow computer vision platform (ROBOFLOW, 2023), a cloud-based infrastructure that provides streamlined tools for dataset annotation, pre-processing, model training, and deployment. Roboflow was selected for training due to its integrated pipeline that simplifies the training process, offers automatic data augmentation, and provides efficient model versioning and deployment capabilities (GALLAGHER, 2023). It also facilitates real-time model performance monitoring and allows for rapid iteration during model development,

Table 1: Summary of methodologies, strengths, weaknesses, and results in cattle monitoring research.

Reference	Methodology	Strength and Weakness	Result
Nasirahmadi, Edwards e Sturm (2017)	Image processing techniques monitor cattle behavior and parameters like weight, health, movement, and eating patterns.	Machine learning methods were used to identify cattle behavior but were unable to validate the model based on performance metrics such as precision, recall, accuracy, and F1 score	Accuracy of the classifier was 95.6%
Nie et al. (2024)	Yolo5 was used for emotion detection in pig faces using changes in the eyes, lips, ears, and nose.	The model classified four emotional states: happy, neutral, fear, and anger. The dataset was not balanced across all types of emotional states.	Mean average precision was 89.4%
Sarwar et al. (2021)	Fully connected network was used along with AlexNet, GoogleNet, VGG16, VGG19, and ResNet50 for identifying sheep in UAV images.	The model recognizes sheep in UAV images from 80 m and 125 m above the ground but cannot monitor sheep behavior.	The recall value of this system was in the range from 90% to 98%.
Dutta et al. (2022)	An IoT device mounted on dairy cattle's neck monitors activities using extreme gradient boosting and random forests classifiers.	The model accurately classified the animal's activities such as "standing", "lying", "walking", "standing and ruminating", "lying and ruminating"and "walking and ruminating", but it is an invasive method.	This model achieves an accuracy of 97% with good recall and precision.
Sant'Ana et al. (2021)	Predicting the weight of sheep from their image using computer vision and regression.	This model predicts the weight of sheep in a non-invasive way from its image. It uses parameters such as area, perimeter, minor axis, major axis, extreme points associated with Euclidean distance, equivalent diameter, strength, Hu- moments, aspect ratio, and K-curvature.	It measures weight with a mean error of 3.1 kg.
Liu, He e Norton (2020)	Predicting a cow's body condition score (BCS) using computer vision.	This model uses a Gaussian mixture to separate the cow from the background. This model extracts local and global features to measure the BCS accurately and uses an ensemble model to deal with an imbalanced dataset.	This model achieved an accuracy of 95% within a deviation of 0.5 points.

which is particularly valuable for comparative studies involving multiple architectures.

4 Results and discussion

The YOLOv8 emotion recognition model on Roboflow completed its training with 3040 images in 12 minutes and achieved only 70.6% accuracy in classifying images of sheep, whether they were in pain or not. Pre-trained models such as ResNet50, ResNet101, ResNet152, VGG16, and EfficientNet perform better than the YOLOv8 model because they have a more profound architecture to extract the higher-level features when compared to YOLOv8.

The pre-trained models EfficientNet, ResNet50, ResNet101, ResNet152 and VGG16 were trained on a limited dataset with only 200 images of size $(200 \times 200 \times 3)$ for 25 epochs, their performance was evaluated and gave encouraging results. The results of the EfficientNet emotion detector, alongside its accuracy and loss learning curves, are shown in Table 2. The model achieves 89% precision, 85% recall and 87% F1-score for "sheep without pain"and 86% precision, 90% recall and 88% F1-score for "sheep in pain", overall accuracy 88% with 40 samples. Table 2 presents EfficientNet Model Performance Metrics.

We then use ResNet variants ResNet50, ResNet101 and deep convolution architecture ResNet152 for emotion detection and find that the overall accuracy of the model is between 88% and 90%. Table 3 shows the results and learning curves of the ResNet50 emotion detector. The model achieves 87% precision, 100% recall and 93% F1-score for "sheep without pain"and 100% precision, 85% recall and 92% F1-score for "sheep with pain".

Furthermore, Table 4 shows its precision, recall, F1-Score, and corresponding learning curves. The ResNet101 model achieves 83% precision, 100% recall, and 91% F1-Score for "Sheep without pain"and 100% precision, 80% recall, and 89% F1-Score for "Sheep with pain".

Again, Table 5 shows its precision, recall, F1-Score

Category	Precision (%)	Recall (%)	F1-Score (%)	Count
0: Without pain	89	85	87	20
1: With pain	86	90	88	20
Accuracy	-	-	88	40
Macro Average	88	88	87	40
Weighted Average	88	88	87	40

Table 2: EfficientNet Model Performance Metrics.

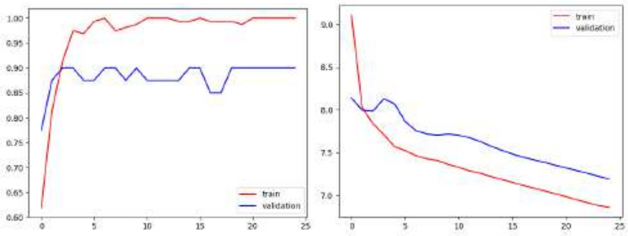

Figure 6: Accuracy (left) and loss (right) curves for the EfficientNet Model.

Category	Precision (%)	Recall (%)	F1-Score (%)	Count
0: Without pain	87	100	93	20
1: With pain	100	85	92	20
Accuracy	-	-	93	40
Macro Average	93	93	92	40
Weighted Average	93	93	92	40

Table 3: ResNet50 Model Performance Metrics.

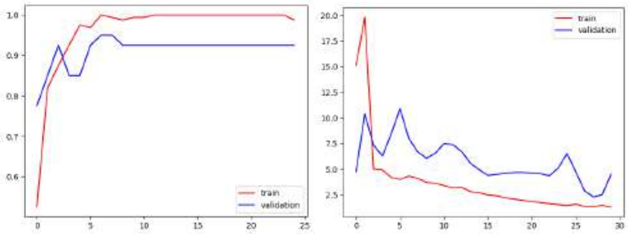

Figure 7: Accuracy (left) and loss (right) curves for the ResNet50 Model.

Category	Precision (%)	Recall (%)	F1-Score (%)	Count
0: Without pain	83	100	91	20
1: With pain	100	80	89	20
Accuracy	-	-	90	40
Macro Average	92	90	90	40
Weighted Average	92	90	90	40

Table 4: ResNet101 Model Performance Metrics.

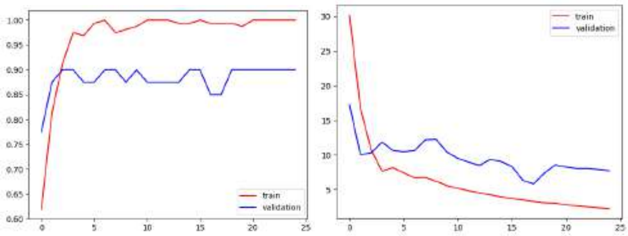

Figure 8: Accuracy (left) and loss (right) curves for the ResNet101 Model.

Category	Precision (%)	Recall (%)	F1-Score (%)	Count
0: Without pain	86	90	88	20
1: With pain	89	85	87	20
Accuracy	-	-	88	40
Macro Average	88	88	87	40
Weighted Average	88	88	87	40

Table 5: ResNet152 Model Performance Metrics.

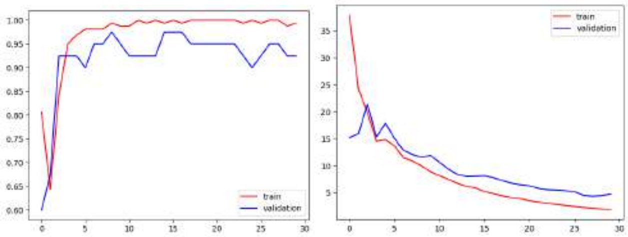

Figure 9: Accuracy (left) and loss (right) curves for the ResNet152 Model.

Category	Precision (%)	Recall (%)	F1-Score (%)	Count
0: Without pain	80	100	89	20
1: With pain	100	75	86	20
Accuracy	-	-	88	40
Macro Average	90	88	87	40
Weighted Average	90	88	87	40

Table 6: VGG16 Model Performance Metrics.

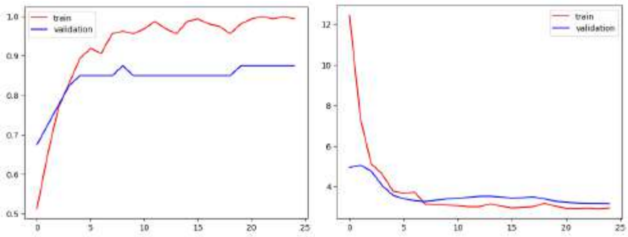

Figure 10: Accuracy (left) and loss (right) curves for the VGG16 Model.

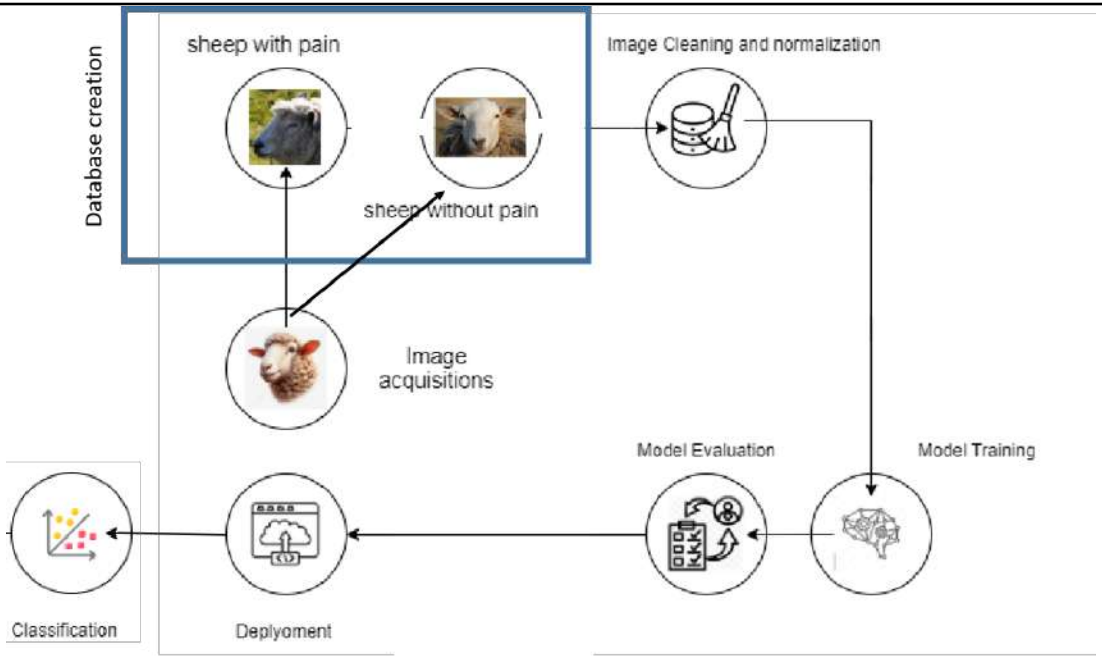

Figure 1: Process of development and deployment of an emotion detection model for sheep based on images.

Figure 2: Examples of images of sheep without pain.

Figure 3: Examples of images of sheep with pain.

details, and learning curves. The ResNet152 model achieves 86% precision, 90% recall and 88% F1 score for "Sheep without pain"and 89% precision, 85% recall and 87% F1 score for "Sheep in pain".

Finally, we trained VGG16 on the same dataset and found interesting results in emotion detection. Table 6 shows its precision, recall, F1 score, and learning curves in detail. The VGG16 model achieves 80% precision, 100% recall, and 89% F1 score for "Sheep without pain"and 100% precision, 75% recall, and 86% F1 score for "Sheep in pain".

Despite this progress, several challenges and limitations remain. Data quality and annotation are essential for training effective deep learning models. Collecting and labeling high-quality datasets can be labor-intensive and require domain expertise, particularly in recognizing subtle, species-specific behaviors. Additionally, the computing resources required to train and deploy deep learning models can be a barrier for small farms or operations with limited access to advanced technologies. Ensuring the generalizability of these models to different environments and species is another ongoing challenge, as models trained on specific datasets may not perform well under various conditions.

In the future, multimodal data integration – combining visual data with audio and physiological signals – may improve the accuracy and robustness of emotion and behavior detection models. Implementing continuous learning mechanisms will allow these models to adapt and improve as new data becomes available, increasing their effectiveness. Ethical considerations

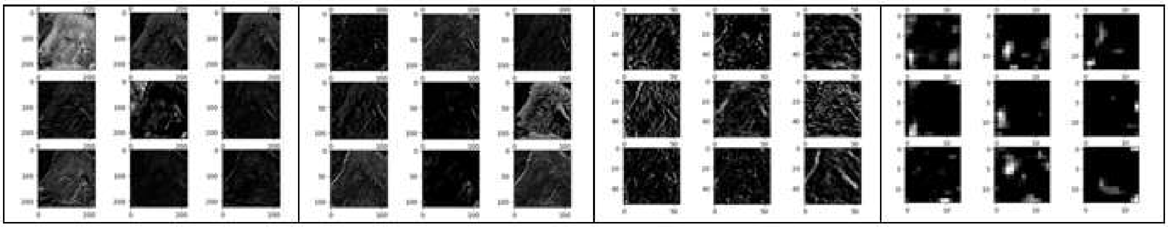

Figure 4: Feature extraction of sheep with pain at layers 2, 4, 8, and 16 through VGG16.

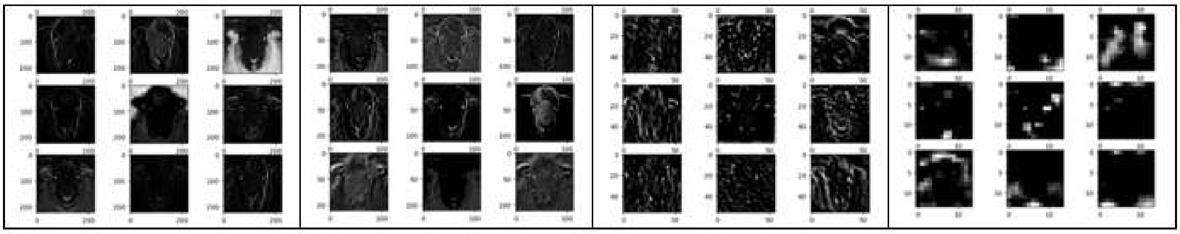

Figure 5: Feature extraction of sheep without pain at layers 2, 4, 8, and 16 through VGG16.

must also be taken into account to ensure that the deployment of these technologies prioritizes animal welfare and humane treatment.

5 Conclusion

Applying deep learning architectures in livestock agriculture offers a promising approach for improving animal observation, management, and welfare. In this work, we demonstrated that neural networks such as EfficientNet, ResNet50, ResNet101, ResNet152, and VGG16 are effective in recognizing pain in sheep. These models achieved accuracy rates ranging from 88% to 93% on our test set, outperforming YOLOv8, which achieved an accuracy of 70.6%. While YOLOv8 is widely used in object detection tasks, the feature extraction capabilities of the evaluated models make them better suited for identifying the subtle facial indicators associated with emotion detection in sheep.

Deep Convolutional Neural Networks (CNNs) have proven effective in various livestock monitoring tasks, from animal detection in aerial images to anatomical segmentation. Utilizing computer vision, our proposed models demonstrate the feasibility of recognizing sheep emotional states, offering a non-invasive technique to assist in pain evaluation.

While the initial test results are encouraging, it is important to note that the models were evaluated on a relatively small test set (40 images) and currently lack broader statistical validation. Because of this limited sample size, expanding the dataset will be essential to accurately gauge the models' operational efficiency on a farm. In the future, this approach could potentially be generalized to detect other states, such as heat stress, hunger, or fear, provided that datasets specifically designed for these states are created. Expanding dataset size and diversity will be critical to enhancing the models' accuracy and robustness in real-world scenarios.

Challenges remain in several key areas. Data quality and annotation are critical for training effective deep learning models, as collecting and labeling high-quality datasets is labor-intensive and requires domain expertise. Computational resource requirements may also pose a barrier, especially for smaller farms or operations with limited technological infrastructure. Moreover, ensuring the generalizability of these models to different environments and species remains an ongoing challenge, as models trained on specific datasets may not perform consistently under varying conditions.

Future research directions should focus on validating these models on larger datasets and integrating multimodal data, such as combining visual information with audio signals or physiological data, to improve the robustness of emotion detection. Continuous learning mechanisms can enable models to adapt and improve over time with new data, ensuring better performance in diverse scenarios. Additionally, ethical considerations must remain at the forefront, ensuring that the deployment of these technologies prioritizes animal welfare and humane treatment while addressing the challenges of a growing global demand for animal products.

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