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Article

Automatic Identification of Aceh Cattle Using an Image-Based Computer Vision Approach for Smart Livestock Management

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Abstract: The identification of cattle breeds is an important aspect of livestock management, particularly for maintaining genetic resources and supporting breeding programs of local cattle. In Indonesia, Aceh cattle represent one of the important indigenous breeds whose identification is commonly conducted through manual observation based on physical characteristics. However, conventional identification methods often depend on human expertise and may lead to inconsistencies or misclassification. Recent advances in artificial intelligence, especially in computer vision technologies, provide new opportunities to develop automated systems for livestock identification. This study aims to develop an image-based classification model to distinguish Aceh cattle from non-Aceh cattle using computer vision techniques. A dataset of cattle images was collected from field documentation and various online sources and categorized into two classes. After the image collection process was completed, image adjustment and augmentation processes followed, resulting in a final dataset of 2,360 images, which were used for model training and testing. The dataset consisted of 800 original images expanded through augmentation techniques and was automatically divided into training and validation datasets using an 80:20 ratio. The classification model was developed using Teachable Machine and evaluated using performance metrics such as accuracy, precision, and recall. The experimental results show that the model achieved an accuracy of 89.6%, with precision and recall values of 89.1% and 90.3%, respectively. The findings demonstrate the feasibility of applying low-code artificial intelligence platforms for indigenous cattle breed classification in digital livestock management systems.

Keywords: Aceh Cattle; Computer Vision; Image Classification; Livestock Identification; Smart Agriculture; Precision Livestock Farming

1. Introduction

Livestock plays an important role in supporting food security and the agricultural economy in many countries. Livestock production, particularly cattle farming, is one of the main sources of animal protein that contributes to meeting the nutritional needs of the population while also increasing farmers' income. In Indonesia, various local cattle breeds represent valuable genetic resources because they contribute to the national beef production system and provide livelihoods for rural communities. One of the important indigenous cattle breeds is Aceh cattle [1], which is well known for its strong adaptability to tropical environmental conditions and its ability to survive under limited feed availability [2].

Accurate identification of cattle breeds is an important aspect of breeding management, conservation programs, and livestock productivity improvement [3]. Proper identification enables farmers and researchers to monitor cattle populations, maintain genetic purity, and improve the efficiency of livestock production systems. However, the identification process is generally carried out manually based on morphological characteristics or physical traits of the animals. This approach relies heavily on human observation and experience, which may lead to subjectivity and inconsistencies in the identification process.

With the rapid development of digital technologies, the application of artificial intelligence in the agricultural sector has grown significantly. One of the widely used technologies is Computer Vision, which allows computers to extract and interpret information from digital images. This technology has been widely applied in precision agriculture systems, including crop monitoring, plant disease detection, and livestock management. Previous studies have shown that machine learning and deep learning techniques can be used to automatically identify livestock by analyzing specific visual patterns from animal images [4]. A systematic review on machine learning-based cattle identification indicated that methods such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and various visual feature extraction techniques have been widely applied to improve the accuracy of livestock identification systems, Previous studies on cattle breed classification commonly reported classification accuracies ranging from 85% to above 95%, depending on dataset complexity, image quality, and deep learning architecture used [5].

Although numerous studies have explored the application of artificial intelligence and computer vision techniques for livestock identification, most existing research focuses on individual animal recognition, biometric identification, or breed classification using datasets from commercial or widely studied cattle breeds. Studies specifically addressing the classification of indigenous cattle breeds, particularly Aceh cattle, remain limited. In addition, Aceh cattle share several morphological similarities with other local and crossbred cattle commonly found in Indonesia, including similarities in body size, coat color distribution, and body conformation. These overlapping visual characteristics increase the complexity of image-based breed classification and make automated identification more challenging. Previous research related to Aceh cattle has mainly focused on genetic analysis, reproduction performance [6], and feeding management [7] rather than the development of automated identification systems.

This limitation indicates a research gap in the application of image-based artificial intelligence techniques for identifying local Indonesian cattle breeds. Considering the importance of preserving local genetic resources and improving livestock management efficiency, the development of an automated identification system for Aceh cattle becomes highly relevant. The novelty of this research lies in the development of a computer vision-based classification approach specifically designed for Aceh cattle identification using an augmented image dataset.

Contributions of This Study

The major contributions of this study include:

- Development of an Aceh cattle image dataset collected from multiple image sources;
- Application of a low-code computer vision platform for indigenous cattle classification;
- Evaluation of image-based binary classification performance for Aceh cattle identification;
- Demonstration of the potential use of artificial intelligence technologies in smart livestock management systems.

Therefore, this study aims to develop an image-based classification model capable of distinguishing Aceh cattle from non-Aceh cattle using computer vision techniques. The classification model is trained using a dataset of cattle images that has been processed through data augmentation techniques to increase dataset variability. The performance of the model is then evaluated using classification performance metrics such as accuracy, precision, and recall. The results of this study are expected to demonstrate the potential application of artificial intelligence in supporting livestock identification and the development of digital agriculture systems.

The remainder of this paper is organized as follows. Section 2 describes the materials and methods used in this study, including dataset preparation, preprocessing, augmentation, and model training procedures. Section 3 presents the experimental results and model evaluation. Section 4 discusses the implications, limitations, and future research directions. Finally, Section 5 concludes the study.

2. Materials and Methods

2.1. Research Location

The research consisted of two main stages: image dataset collection and artificial intelligence model development. The cattle image dataset was obtained through a combination of field documentation and online image sources, while the artificial intelligence model training process was carried out using an online machine learning platform, Teachable Machine, which enables the development of image classification models without advanced programming requirements [8].

A field image collection of Aceh cattle was conducted across 11 different locations in Aceh Province, Indonesia. These locations included three municipalities—Banda Aceh, Lhokseumawe, and Langsa—as well as eight regencies, namely Pidie, Pidie Jaya, Bireuen, North Aceh, East Aceh, West Aceh, Aceh Besar, and Aceh Jaya. These sampling locations were selected based on the primary development and distribution areas of Aceh cattle within Aceh Province, where the breed is commonly raised by smallholder farmers under traditional livestock production systems [9]. Collecting images from multiple geographical locations was intended to capture variations in environmental conditions, lighting, animal posture, and background settings, thereby improving the diversity and representativeness of the dataset used for model training.

A total of field observations and photographic documentation were conducted using smartphone cameras to capture images of cattle from various angles, including lateral body views and standing positions that clearly displayed the morphological characteristics of the animals. The spatial distribution of the image collection sites across Aceh Province is presented in **Figure 1**, which illustrates the geographic locations where Aceh cattle images were obtained for this study.

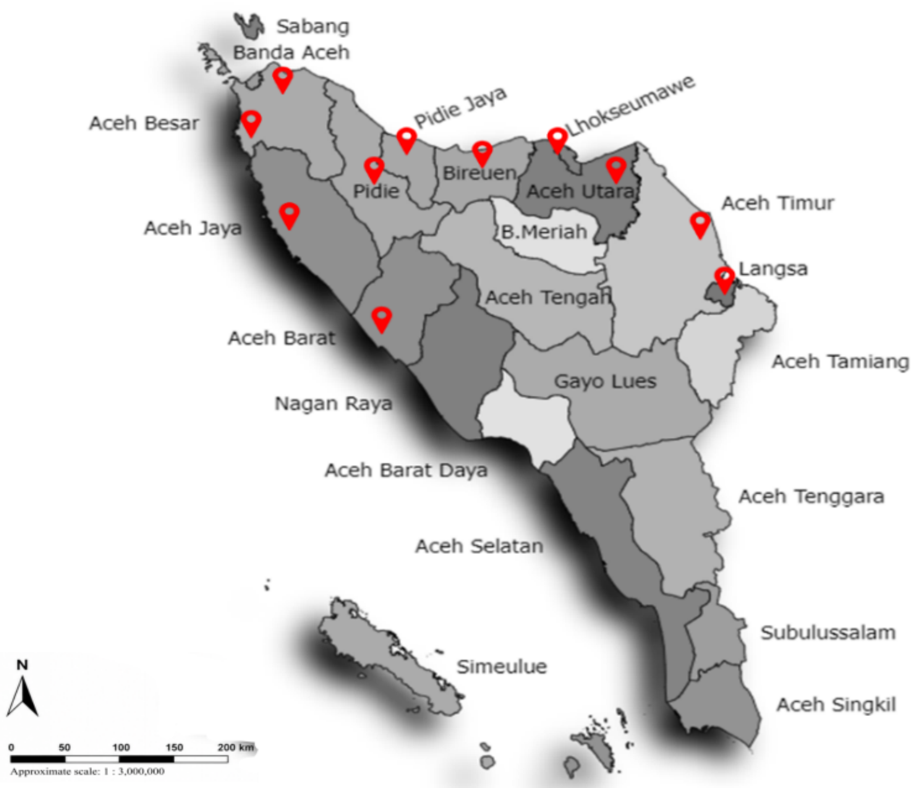

Figure 1. Map of sampling locations for Aceh cattle image dataset collection in Aceh Province, Indonesia.

2.2. Image Dataset Collection and Pre-Processing

The dataset used in this study consisted of digital cattle images categorized into two classes: Aceh cattle and non-Aceh cattle. The non-Aceh category included several cattle breeds commonly found in Indonesia and other regions, namely Bali cattle, Madura, Pesisir, Simmental, Limousin, Brahman, Ongole, Sahiwal, and Holstein Friesian cattle. Images of Aceh cattle were primarily obtained through field documentation conducted in several regions of Aceh Province, Indonesia. Meanwhile, images of non-Aceh cattle were collected from publicly available online sources in order to increase dataset diversity and represent different cattle morphological characteristics. The use of multiple image sources was intended to improve the variability of the dataset and enhance the generalization capability of the classification model.

To maintain dataset quality and relevance, several selection criteria were applied when collecting and selecting images. First, the image had to clearly display the body of the cattle. Second, the body posture of the animal needed to be predominantly visible from the lateral (side) view, which allows morphological characteristics such as body shape and color patterns to be observed more clearly. Third, the image resolution had to be sufficiently high to capture visible morphological features of the cattle. Finally, images containing severe visual disturbances such as excessive blur, heavy occlusion, or extreme lighting conditions were excluded from the dataset. Prior to the model training process, all collected images underwent a data pre-processing stage to improve the overall quality and consistency of the dataset. The pre-processing steps included:

1. Removal of blurred, unclear, or visually distorted images;
2. Resizing images into uniform dimensions to ensure dataset consistency;
3. Cropping irrelevant image areas to focus on cattle body features;
4. Organizing images into their respective class categories.

During the resizing process, all images were standardized to a resolution of 224 × 224 pixels, which is commonly used in image classification tasks in computer vision. This standardization ensures that each image has consistent dimensions when processed by the classification model [10]. Additionally, resizing reduces computational complexity while preserving important visual features such as body structure, color distribution, and morphological characteristics of the animals.

The main objective of the preprocessing stage was to improve dataset consistency so that the artificial intelligence model could learn visual patterns more effectively during the training process. After preprocessing, the images were organized into two primary classes, namely "Aceh cattle" and "non-Aceh cattle." The overall research workflow used for developing the cattle image classification model is illustrated in **Figure 2**. The workflow consisted of image dataset collection, data preprocessing, deep learning model training using Teachable Machine, and model performance evaluation. The composition of the cattle image dataset used in this study is presented in **Table 1**. Examples of cattle images used in the dataset are presented in **Figure 3**.

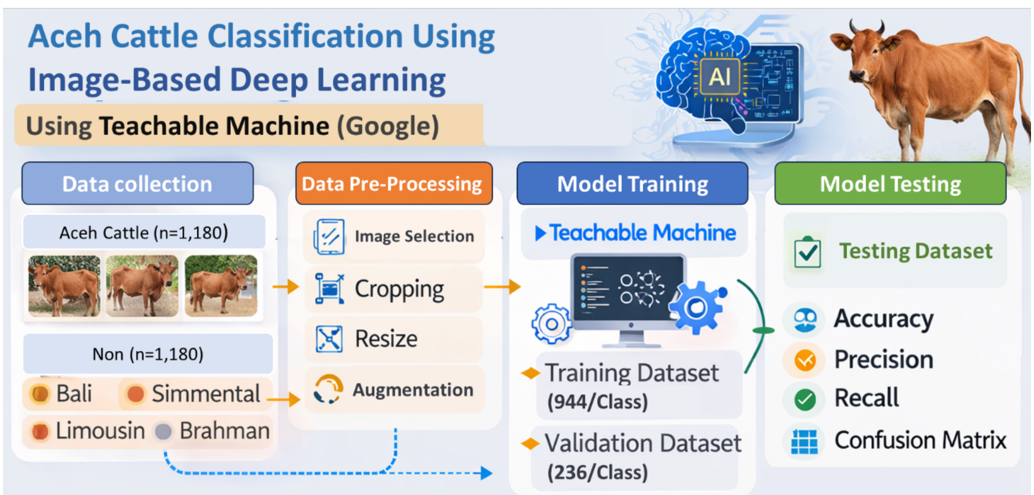

Figure 2. Research workflow for image-based classification of Aceh cattle using a deep learning approach.

Table 1. Composition of the cattle image dataset used in the study.

Category	Original Images	Augmented Images	Total
Aceh Cattle	400	780	1,180
Non-Aceh Cattle	400	780	1,180
Total	800	1,560	2,360

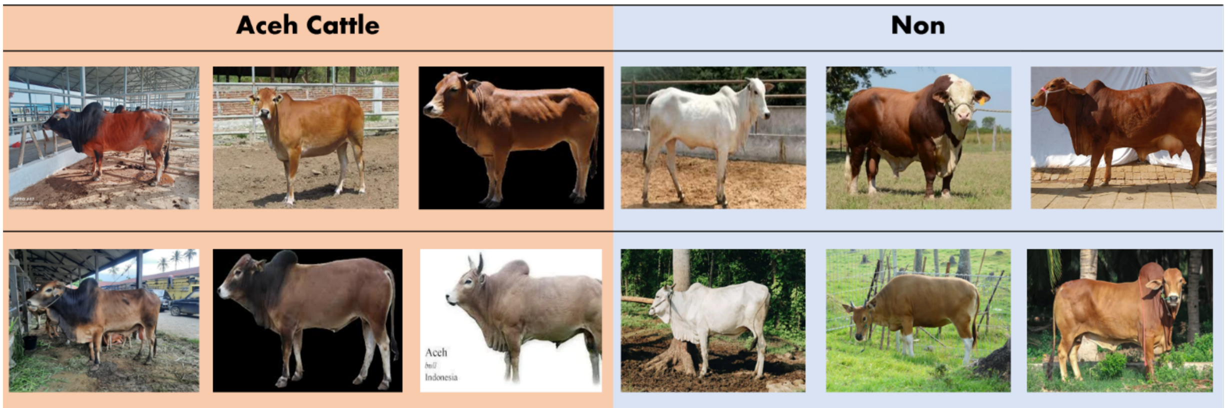

Figure 3. Examples of cattle images used in the dataset.

The original dataset consisted of field-collected and publicly accessible online images. Data augmentation techniques were applied to increase dataset diversity and improve model robustness during the training process. To minimize data leakage, images of the same animal individual were not intentionally distributed across different subsets whenever duplicate similarity could be identified. Manual inspection was conducted during dataset organization to reduce repeated image similarity between training and validation datasets. Online images were collected only from publicly accessible sources intended for educational or research purposes. Images with unclear breed information, excessive watermarking, or poor visual quality were excluded from the dataset. Field images were captured using smartphone cameras with resolutions ranging from 12 to 48 megapixels under outdoor farming conditions during daytime observations. Most images were collected under natural lighting conditions between 08:00 and 17:00 local time.

2.3. Data Augmentation

To improve dataset diversity and enhance the robustness of the image classification model, several data augmentation techniques were applied to the original cattle image dataset. Data augmentation generates additional variations of existing images, allowing the model to learn more generalized visual patterns and improving its ability to classify images captured under different conditions. The augmentation techniques used in this study included the following transformations [11]:

- Random Rotations: Images were randomly rotated within a range of −30° to +30° to simulate variations in camera angles during image acquisition. This transformation allows the model to recognize cattle images even when the animals appear slightly tilted or captured from different orientations in real-world field conditions.
- Horizontal Flipping: Images were randomly flipped along the horizontal axis to represent natural variations in cattle body orientation, such as when animals face different directions relative to the camera. This ensures that the model learns to recognize cattle morphology regardless of the direction the animal is facing.
- Brightness Adjustment: Random brightness modifications within a range of ±20% were applied to simulate variations in lighting conditions during image capture. This includes images taken under direct sunlight, cloudy weather, shade, or different times of the day. These adjustments help improve the model's ability to perform consistently under diverse environmental lighting conditions.
- Zoom and Random Cropping: Zooming transformations of up to 10% and random cropping were applied to simulate variations in camera distance and partial object visibility. This technique allows the model to remain

robust when the entire body of the cattle is not perfectly centered or when images are captured from varying distances.

- Minor Image Translation: Small positional shifts were applied to some images to simulate slight camera movement or variations in object positioning within the frame. This transformation helps the model learn spatial invariance and improves its ability to detect cattle features even when the subject is not centrally positioned.

Through these augmentation techniques, additional image variations were generated from the original dataset. As a result, the dataset size increased from 800 original images to a total of 2,360 images used in the model training process. The augmented dataset provides a wider range of visual representations of cattle images, enabling the model to learn more generalized features and improving its classification performance. The application of data augmentation in this study is expected to enhance the ability of the artificial intelligence model to accurately distinguish Aceh cattle from non-Aceh cattle under different visual conditions and image acquisition scenarios.

2.4. Artificial Intelligence Model Training

The image classification model was developed using Teachable Machine, an online platform that utilizes Deep Learning techniques to recognize visual patterns from image datasets. The platform employs artificial neural network architectures to automatically extract relevant visual features from the images and classify them into predefined categories. The model training process was carried out through several main steps:

- Creating an image classification project on the Teachable Machine platform.
- Uploading the prepared image dataset into two classes, namely "Aceh cattle" and "non-Aceh cattle."
- Initiating the automated model training process provided by the platform.
- Saving the trained classification model for further evaluation and testing.

The final dataset consisted of 2,360 images, which were automatically divided by the system into training and validation sets. Approximately 80% of the images were used for training the model, while the remaining 20% were used as the validation dataset. The training data were used to teach the model to recognize visual patterns [12], while the validation data were used to monitor model performance during training and prevent overfitting. After the training process was completed, model performance was evaluated using the validation dataset automatically generated by the Teachable Machine platform. Each test image was input into the system, and the model generated a prediction output in the form of class probability values indicating the likelihood that the image belonged to a particular category. The predicted classification results were then compared with the actual image labels to determine the accuracy of the classification model. These results were further analyzed using several performance evaluation metrics, including accuracy, precision, and recall, to measure the effectiveness of the developed image classification system.

Model Configuration

The Teachable Machine platform utilizes transfer learning techniques based on pre-trained convolutional neural network (CNN) architectures optimized for image classification tasks. However, detailed information regarding internal hyperparameters such as optimizer configuration, learning rate scheduling, hidden layer architecture, and batch size is not fully accessible through the platform interface. In this study, the input image size was standardized to 224 × 224 pixels. The dataset was automatically divided by the platform into training and validation subsets using an 80:20 ratio. The use of Teachable Machine aimed to evaluate the feasibility of low-code artificial intelligence platforms for livestock image classification under limited computational resource conditions.

2.5. Model Evaluation and Analysis

The performance of the trained image classification model was evaluated using several commonly used evaluation metrics in machine learning classification tasks. These metrics were used to measure how well the model can correctly classify images of Aceh cattle and non-Aceh cattle. In this study, the evaluation of the classification model was performed using three main performance indicators, namely accuracy, precision, and recall. These metrics provide quantitative measurements of the model's ability to correctly identify cattle images based on their respective classes. Accuracy represents the proportion of correctly classified images compared to the total number of images evaluated. It provides an overall measure of the classification performance of the model [13].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision measures the proportion of correctly predicted positive observations to the total predicted positive observations. In the context of this study, precision indicates how accurately the model identifies images belonging to the Aceh cattle class [14].

$$Precision = \frac{TP}{TP + FP}$$

Recall measures the proportion of actual positive observations that were correctly identified by the model. This metric reflects the ability of the model to detect Aceh cattle images among all actual Aceh cattle samples [15].

$$Recall = \frac{TP}{TP + FN}$$

In these equations:

- TP (True Positive) represents Aceh cattle images correctly classified as Aceh cattle.
- TN (True Negative) represents non-Aceh cattle images correctly classified as non-Aceh cattle.
- FP (False Positive) represents non-Aceh cattle images incorrectly classified as Aceh cattle.
- FN (False Negative) represents Aceh cattle images incorrectly classified as non-Aceh cattle.

The evaluation metrics were calculated using the results obtained from the test dataset that was not involved in the model training process [16]. The predicted labels generated by the model were compared with the actual image labels to determine the classification performance. In addition, the classification results were summarized using a confusion matrix [17], which provides detailed information regarding correctly and incorrectly classified samples across the two classes. The analysis results were then presented in the form of tables and graphical diagrams to facilitate the interpretation of model performance and to provide a clearer understanding of the classification capability of the developed artificial intelligence system.

3. Results

3.1. Classification Performance

After the training process was completed, the performance of the classification model was evaluated using the validation dataset generated by the Teachable Machine platform. The evaluation metrics used in this study included accuracy, precision, and recall, which are commonly applied in machine learning-based classification studies. The results of the model performance evaluation are presented in **Table 2**.

Table 2. Performance evaluation metrics of image classification model.

Metric	Value (%)
Accuracy	89.6
Precision	89.1
Recall	90.3

The developed classification model achieved an accuracy of 89.6%, indicating that most cattle images were successfully classified into their respective categories. The precision value of 89.1% demonstrates the model's ability to correctly identify Aceh cattle images among predicted positive samples, while the recall value of 90.3% indicates that the majority of Aceh cattle images were successfully detected by the model.

3.2. Confusion Matrix Analysis

To provide a more detailed evaluation of the classification results, a confusion matrix analysis was conducted. The confusion matrix summarizes the number of correctly and incorrectly classified images for each class. The confusion matrix of the developed classification model is presented in **Table 3**.

Table 3. Confusion matrix of the cattle image classification model (n = 472 images).

Actual Class	Predicted Aceh Cattle	Predicted Non-Aceh Cattle
Aceh Cattle	213	23
Non-Aceh Cattle	26	210

The confusion matrix indicates that most Aceh cattle images and non-Aceh cattle images were correctly classified by the model. However, several misclassifications were still observed between the two categories. These classification errors may be associated with similarities in body shape, coat color distribution, and image acquisition conditions among local cattle breeds.

3.3. Prediction Probability Examples

To further illustrate the performance of the developed model, several test images were evaluated using the trained classification system. The model generated prediction outputs in the form of probability values representing the likelihood that a given image belongs to a particular class. Examples of prediction probability results produced by the model are presented in **Table 4**.

Table 4. Example prediction probabilities generated by the classification model.

No	Probability (%)		Prediction
	Aceh Cattle	Non	
1	92	8	Aceh
2	88	12	Aceh
3	20	80	Non
4	15	85	Non
5	76	24	Aceh

The prediction probability results demonstrate that the developed model was generally able to distinguish Aceh cattle from non-Aceh cattle with relatively high confidence values. Higher probability scores indicate stronger model confidence in assigning images to a particular classification category.

4. Discussion

4.1. Interpretation of Model Performance

The results of this study demonstrate that image-based artificial intelligence can effectively distinguish between Aceh cattle and other cattle breeds using visual information extracted from digital images. The developed classification model achieved an accuracy of 89.6%, with precision of 89.1% and recall of 90.3%, indicating that the model was able to correctly identify most images in the validation dataset. These results confirm that morphological characteristics visible in cattle images can be successfully captured and interpreted by deep learning models to support automated breed identification.

The precision and recall values obtained in this study indicate that the developed model was generally able to correctly identify Aceh cattle images with relatively high consistency. Nevertheless, several misclassification cases were still observed, suggesting that visual similarities among cattle breeds remain a challenge for automated image-based classification systems [18,19].

The confusion matrix results provide further insight into the classification performance of the model. From the validation dataset of 472 images, the majority of images in both classes were correctly classified. However, some prediction errors occurred, including Aceh cattle images predicted as non-Aceh cattle and vice versa. Such misclassification cases may occur due to similarities in morphological features among cattle breeds, including body shape, coat color patterns, and structural characteristics that may visually resemble those of Aceh cattle. In addition, variations in lighting conditions, background environments, and animal posture captured in the images may also influence the visual features extracted by the model.

The performance achieved in this study is consistent with previous research demonstrating the effectiveness of computer vision and deep learning approaches in livestock identification. Advances in machine learning techniques have enabled automated systems to analyze complex visual patterns in animal images and use them for classification tasks. The performance achieved in this study is consistent with previous research demonstrating the effectiveness of deep learning approaches for livestock image classification. Earlier studies reported that neural network-based models are capable of learning complex morphological features from cattle images and using them for automated recognition tasks [20,21]. Similar findings were observed in the present study, where the developed model successfully distinguished Aceh cattle from non-Aceh cattle based on visual characteristics extracted from digital images. Deep learning models can effectively recognize cattle breeds and estimate livestock parameters based on image analysis. Their study confirmed that neural networks are capable of learning complex morphological features from cattle images and using them for automated recognition tasks [22]. These findings support the results obtained in the present study, where visual patterns extracted from cattle images were successfully used to distinguish Aceh cattle from other breeds. Other studies have also highlighted the potential of computer vision technologies in livestock systems. Deep learning-based livestock recognition systems can improve animal traceability and monitoring by enabling automated identification through digital images [22]. Such systems reduce the reliance on manual observation and provide more objective and scalable approaches to livestock identification.

The relatively high classification accuracy achieved in this study suggests that distinctive visual characteristics of Aceh cattle were successfully captured by the deep learning model. Aceh cattle generally exhibit recognizable morphological traits, including medium body size, characteristic coat color variations, and body conformation adapted to tropical environments. These morphological attributes provide visual patterns that can be learned by neural networks during the training process [23,24], allowing the model to differentiate Aceh cattle from other breeds included in the dataset.

Overall, the findings of this research support the growing body of literature indicating that artificial intelligence and computer vision technologies can play an important role in livestock management systems. The successful application of image-based classification in this study demonstrates the feasibility of developing automated identification tools for indigenous cattle breeds. Such technologies may contribute to improved livestock monitoring, data recording, and conservation of local genetic resources in livestock production systems.

4.2. Implications for Livestock Identification and Digital Agriculture

The development of automated image-based cattle identification systems has important implications for livestock management and digital agriculture. In many regions, breed identification is still conducted manually through visual inspection by farmers or livestock officers. Although experienced observers may recognize breed characteristics, manual identification methods can be subjective and may lead to inconsistencies in data recording. The use of computer vision technology offers a more objective and standardized approach to livestock identification [25–27].

Image-based classification systems can process large numbers of animal images automatically and provide consistent predictions based on learned visual features. This capability may assist farmers, researchers, and government institutions in monitoring livestock populations, documenting breed distribution, and supporting breeding programs. For indigenous cattle breeds, automated identification systems may also support conservation efforts. Local breeds represent valuable genetic resources that are adapted to specific environmental conditions and management systems. Accurate identification of these breeds is essential for maintaining genetic diversity and ensuring the sustainability of local livestock production systems.

Furthermore, the integration of artificial intelligence technologies into livestock management is closely aligned with the concept of precision livestock farming. In such systems, digital technologies are used to collect and analyze animal-related data to improve productivity, efficiency, and animal welfare. Computer vision technologies have already been applied in several livestock applications, including animal counting, body condition scoring, behavior monitoring, and health assessment [28]. The results of this study indicate that image-based deep learning models can contribute to the development of automated livestock identification tools. Such technologies may support the digital transformation of livestock production systems by enabling more efficient data collection, monitoring, and decision-making processes.

4.3. Limitations and Future Research Directions

Despite the promising results obtained in this study, several limitations should be acknowledged. Although the dataset was expanded through data augmentation, the augmented images were derived from a limited number of original photographs. Consequently, certain variations in environmental conditions, camera angles, and image quality that may occur in real-world livestock environments might not be fully represented in the dataset. Another limitation relates to the classification scope of the model. The model developed in this research focused on a binary classification task distinguishing Aceh cattle from non-Aceh cattle. In practical livestock systems, however, multiple cattle breeds may coexist within the same production environment. Therefore, future studies may explore multi-class classification models capable of identifying several cattle breeds simultaneously [29–31].

Variations in lighting conditions, background complexity, and animal posture may also influence the visual features extracted by the model. These factors may contribute to occasional misclassification cases observed in the validation results [32,33]. Expanding the dataset with more diverse images collected from different environments could help improve the robustness and generalization ability of the model [34,35]. Another limitation of this study is related to the use of the Teachable Machine platform, which provides limited access to advanced model configuration parameters. Detailed settings such as learning rate adjustment, optimizer selection, hidden layer modification, and batch size optimization could not be fully controlled during the training process. Consequently, the developed model may not represent the maximum achievable performance compared to fully programmable deep learning frameworks.

Further improvements may also be achieved through the use of more advanced deep learning architectures and larger datasets. Integrating computer vision approaches with other types of livestock data, such as biometric measurements or sensor-based monitoring systems, may provide additional information that enhances automated livestock identification systems. Overall, continued research in this area will contribute to the development of more robust artificial intelligence tools for livestock identification and support the sustainable management of indigenous cattle genetic resources.

5. Conclusions

This study developed an image-based classification model to distinguish Aceh cattle from non-Aceh cattle using computer vision and deep learning techniques. A total of 2,360 cattle images were utilized through image collection and data augmentation processes. The developed classification model achieved an accuracy of 89.6%, with precision and recall values indicating satisfactory classification performance for automated cattle breed identification. The findings demonstrate that artificial intelligence and computer vision technologies have considerable potential for supporting livestock identification, breed documentation, and the conservation of indigenous cattle genetic resources. The developed approach also highlights the feasibility of utilizing low-code artificial intelligence platforms for livestock classification under limited computational resource conditions.

Despite the promising results, several limitations remain related to dataset variability, environmental image conditions, and the binary classification scope of the model. Future studies are recommended to utilize larger and more diverse datasets, advanced deep learning architectures, and multi-class classification approaches to further improve model robustness and practical applicability in digital livestock management systems.

Author Contributions

Conceptualization, M.A. and Y.Y.; methodology, M.A.; software, M.A.; validation, E.M.S., C.I.N. and M.A.N.A.; formal analysis, M.A.; investigation, H.K. and M.M.; resources, H.K. and M.M.; data curation, E.M.S. and C.I.N.; writing—original draft preparation, M.A. and M.A.N.A.; writing—review and editing, M.A. and E.M.S.; visualization, M.A.; supervision, E.M.S., Y.Y. and M.A.N.A. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Due to image ownership and data collection limitations, the dataset used in this study is available from the corresponding author upon reasonable request. Future work will consider public dataset deposition to support reproducibility and open research practices.

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Conflicts of Interest

The authors declare no conflict of interest.

AI Use Statement

During the preparation of this manuscript, the authors used ChatGPT solely for language refinement and proofreading support. No AI tools were used for data analysis, interpretation, or generation of scientific results. All outputs were critically reviewed and edited by the authors. The authors take full responsibility for the integrity and accuracy of the work.

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