

Development of a Dairy Cattle Facial Recognition System Based on CNN for Digital Livestock Data Management

Andika Muhammad Nur Kholiq^{1*}, Arief Suryadi Satyawan², Mokh Mirza Etnisa Haqiqi³, Arief Abdillah⁴, R Helkhan Sultan Fajar⁵, Yusril Kamil⁶

^{1,3,4,5,6}Program Studi Teknik Elektro, Teknik, Universitas Garut
²Badan Riset dan Inovasi Nasional (BRIN)

Email: 1andikamuhammad643@gmail.com, 2arie021@brin.go.id, 3mirza@uniga.ac.id,
4ariefabdi170012002@gmail.com, 5helkhansultan@gmail.com

Abstract – Dairy cattle data management plays a crucial role in supporting operational efficiency and the sustainability of the livestock sector. However, conventional practices at Mamad Jaya Farm in animal identification still present severe operational and animal welfare challenges. The existing traditional marking methods carry high physical risks for the livestock, frequently leading to torn ears from ear-tagging, severe skin irritation from branding, and high human-error risks in manual paper-based record-keeping. To mitigate these invasive drawbacks, this study aims to develop an artificial intelligence-based facial recognition system for dairy cattle as a non-invasive solution to support digital and integrated livestock data management. A Convolutional Neural Network (CNN) architecture was uniquely implemented for the identification process due to its superior capacity to automatically and hierarchically extract complex spatial biometric features from facial images without manual feature engineering. The research methodology involved collecting a multi-angle facial dataset from a herd of 15 dairy cattle at Mamad Jaya Farm, Karangpawitan, Garut, which was then processed using Roboflow. The developed model was integrated into a web-based livestock platform named BonvaLink. Empirical testing on 15 distinct cattle facial images demonstrated that the system achieved an individual identification accuracy of 93.33%, with the majority of correct predictions yielding robust confidence scores. These results indicate that the CNN-based biometric approach is highly effective and reliable in recognizing individual dairy cattle identities under practical barn environments

Keywords – Cow facial identification, Artificial Intelligence, CNN, Livestock Data Management, Computer Vision, Machine Learning, Smart Farming.

I. INTRODUCTION

The dairy cattle sector plays a strategic role in supporting food security and meeting the global demand for animal-based protein, particularly through milk production[1]. The success of modern dairy farm management is determined not only by feed quality and animal health, but also by the integration of accurate, structured, and sustainable digital livestock data management systems[2]. Individual cattle identification is a fundamental element in modern livestock administration, as it is directly related to the recording of essential information such as age, health status, vaccination history, daily milk productivity, and artificial insemination records[3]. Inaccuracies in individual identification can lead to severe data overlap and recording errors, which adversely affect managerial decision-making and decrease the overall operational efficiency of dairy industries[4].

In conventional dairy farming practice, individual identification is generally performed manually through invasive physical methods such as ear tagging, hot iron branding, neck chains, or writing identification numbers directly on the animal's skin[5]. Although these methods have been widely applied for decades, various recent veterinary studies indicate that physical identification presents significant drawbacks, particularly regarding animal welfare (*kesrawan*)[6]. Ear tagging frequently induces tissue inflammation, deep wounds, tears, and an increased risk of bacterial infection, whereas hot iron branding can induce prolonged psychological stress, severe burns, and long-term health disturbances[7]. Such conditions violate the fundamental principles of animal

welfare, which are increasingly legislated and strictly emphasized in modern smart farming protocols[8]. Furthermore, traditional livestock data recording that still relies on paper-based ledger books poses considerable risks, including data vulnerability to physical loss, ambient moisture damage, and high human-error transcription rates[9]. Therefore, shifting toward a paperless, digitized, and non-invasive biometric identification system has become an urgent necessity to address these continuous challenges[10].

Recent breakthroughs in artificial intelligence (AI) and computer vision have opened new horizons for developing accurate, animal-friendly, and non-invasive livestock biometric systems[11]. Image-based biometrics, particularly facial recognition, are being adapted from human surveillance architectures to precision livestock farming (PLF) applications[12]. Each cow's face possesses unique visual characteristics such as distinct coat pattern distributions, muzzle texture lines, and structural eye-to-nose geometry that serve as natural, immutable identity markers without requiring any physical intervention[13]. However, the implementation of computer-vision-based cattle face recognition still faces critical barriers in small- and medium-scale farms due to limited local dataset repositories, unpredictable ambient barn illumination, and irregular head-tilt movements during data acquisition[14]. Moreover, a majority of previous deep learning studies have focused strictly on isolated algorithmic accuracy without bridging the technology into an applicable, web-based digital platform that farmers can directly interact with[15].



To address these limitations, this study presents an integrated framework featuring an artificial-intelligence-based dairy cattle facial recognition system paired with a web-based management platform named "BonvaLink". This research was empirically conducted at Mamad Jaya Farm, a specialized dairy production farm located in Karangpawitan District, Garut Regency, West Java, Indonesia[16]. As a prominent local milk supplier in the region, Mamad Jaya Farm manages a specific herd consisting of 15 productive dairy cattle (*Bos taurus*). The constrained herd size and manual environment at this facility represent typical challenges faced by small-to-medium Indonesian dairy operations, making it an ideal testing ground for digital transformation.

To process the facial biometrics of the herd, this study deploys a standalone Convolutional Neural Network (CNN) architecture as the core methodology. CNN is specifically selected due to its remarkable capability in automatically and hierarchically extracting spatial features directly from digital images without requiring manual feature engineering[17]. The applied architecture structurally consists of multiple main[18] components, including convolutional layers to extract critical facial patterns[19], pooling layers to reduce data dimensionality and computational complexity[20], and fully connected layers to classify individual cattle identities[21]. This foundational CNN framework provides high efficiency and accuracy in handling complex visual variations under practical barn conditions. By linking the CNN-based identification outputs directly with a digitalized livestock record platform, this system is expected to replace conventional invasive marking methods with a safer, biosecure, and reliable management approach[22]. Ultimately, this research aims to support the digital transformation, traceability, and operational efficiency of small-scale dairy farm management.

II. RESEARCH METHODOLOGY

A. Proses Diagram

The research methodology for this artificial intelligence-based cattle face identification system was systematically designed to ensure that data processing, model training, and result presentation could be carried out in a structured and integrated manner. The system workflow begins with the collection of cattle facial image data, followed by initial data preprocessing, the identification process using an artificial intelligence model, and the storage and display of identification results through a website interface.

The process diagram used in this study is presented in Figure 1, which illustrates the relationship among the input, process, and output components of the system. The diagram shows how cattle facial images, as input, are processed through preprocessing and identification stages using a deep learning model, resulting in cattle identity output that is stored in a database and displayed through a web-based system.

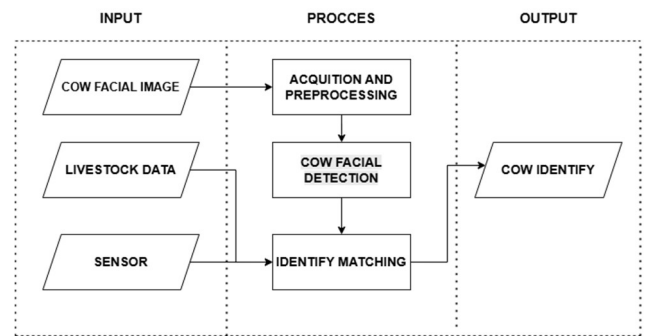


Figure. 1 Research proses flow

B. Dataset

The dataset utilized in this study comprised facial images of 15 individual dairy cattle collected directly from Mamad Jaya Farm, located in Karangpawitan, Garut Regency. For each individual subject, a total of 50 images were captured from multiple viewpoints, specifically incorporating frontal, lateral (side), superior (top), and inferior (bottom) angles. This multi-angle data acquisition strategy was intentionally implemented to provide comprehensive spatial feature variations, compensating for the fluctuating lighting conditions and diverse facial expressions encountered within the real barn environment. An example of the gathered dairy cattle facial image dataset is displayed in Figure 2.



Figure. 2 Dataset used in the study

Following the initial acquisition, the raw dataset was processed using the Roboflow platform for data organization, definitive multi-class labeling, and image augmentation. The core dataset was systematically split into a ratio of 80% for model training and 20% for model validation. Meanwhile, a separate testing dataset consisting of 15 distinct images was allocated for final model evaluation. This testing subset was rigorously designed by extracting exactly one unique, unseen image from each different cow to guarantee unbiased and objective individual identification testing.

C. Research Model Architecture

The cattle face identification model in this study was developed using a Convolutional Neural Network (CNN) architecture. CNN was selected due to its strong capability in extracting spatial features from digital images, making it suitable for object recognition and image-based identification tasks, including cattle facial recognition. The CNN architecture employed consists of several main layers, namely convolutional layers to extract important features from the image, pooling layers to reduce data dimensionality and computational complexity, and fully connected layers to perform cattle identity classification. The CNN model structure applied in this study is presented in Figure 3, which illustrates the image data processing flow from the input stage to the output stage, producing the predicted identity results.



Figure 3 CNN-Based model architecture

D. Website Deployment and Integration

As a practical implementation of the proposed system, the developed cattle face identification model was integrated into a website-based platform. This website functions as a dairy cattle data management system as well as the primary user interface for conducting identification and monitoring livestock data.

The homepage of the website was designed to provide general information and the main system navigation. Furthermore, the system includes a dedicated page displaying cattle data, including identity information and livestock history, as presented in Figure 4.

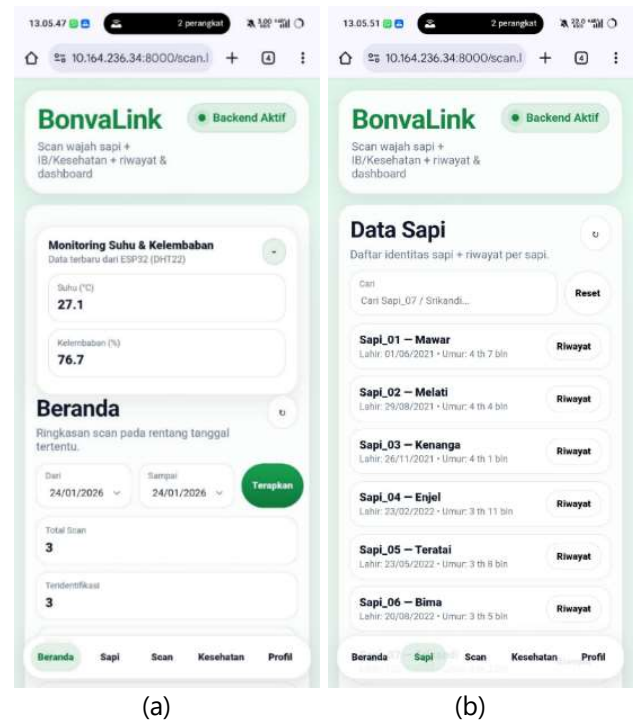


Figure 4 (a) Home page display; (b) Display of cattle data on the website

The cattle face identification process is performed through the main scanning page, where users can capture cattle facial images directly for system-based identification. The interface of the scanning page is presented in Figure 5. After the identification process is completed, the system displays the prediction results, including the recognized cattle identity along with other supporting information, on the prediction results page, as shown in Figure 5.

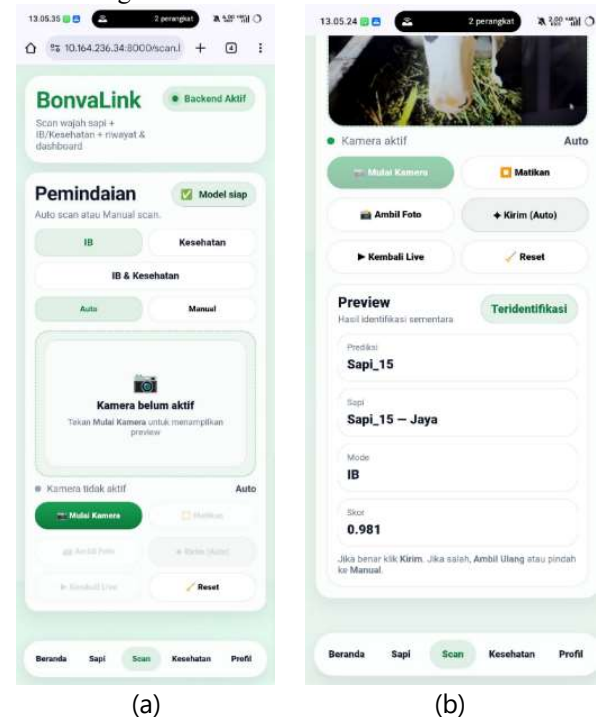


Figure 5 (a) the scanning page interface; and (b) the prediction results display.

III. RESULTS AND DISCUSSION

The performance of the developed Convolutional Neural Network (CNN) model for dairy cattle facial recognition was empirically evaluated using a testing dataset containing 15 sample images. The comprehensive classification metrics, including the predicted classes, confidence scores, and validation status for each testing subject, are systematically compiled in Table 1. Additionally, the qualitative bounding box localization outputs alongside their corresponding identity predictions and probability values are visually presented in Figure 6.

Table 1. Research prediction result value

INPUT FIGURE	RESULT	PRECISION	VALIDATION
COW 1	COW 1	0,66	True
COW 2	COW 2	0,72	True
COW 3	COW 3	0,69	True
COW 4	COW 4	0,64	True
COW 5	COW 5	0,75	True
COW 6	COW 6	0,69	True
COW 7	COW 7	0,66	True
COW 8	COW 8	0,64	True
COW 9	COW 9	0,70	True
COW 10	COW 10	0,62	True
COW 11	COW 11	0,59	True
COW 12	COW 12	0,67	True
COW 13	COW 13	0,49	True
COW 14	Unknown	Unknown	False
COW 15	COW 15	0,66	True

Based on the quantitative results illustrated in Table 1, the proposed system demonstrated a commendable identification performance, achieving an overall accuracy of 93.33% by successfully recognizing 14 out of the 15 tested dairy cattle. The system yielded a relatively low prediction error rate of 6.67%. The majority of the true positive classifications exhibited robust confidence metrics exceeding 0.60, indicating that the underlying deep learning architecture effectively extracted distinct spatial features and biometric facial configurations from the subjects. Specifically, the highest identification confidence was recorded for COW 5 with a score of 0.75, which can be attributed to optimal lighting conditions and an ideal frontal head orientation during image acquisition. Conversely, a lower yet successful confidence score was observed for COW 13 at 0.49, indicating spatial variations or minor occlusions within the feeding area that slightly degraded the model's prediction intensity.

Despite the high success rate, a distinct classification failure occurred in the case of COW 14. As documented in Table 1 and highlighted by the red bounding box indicator in Figure 1, the model failed to align the facial biometric landmarks of COW 14 with any pre-existing identities within the local database repository, subsequently categorizing the subject as "Unknown" with a minimal confidence threshold of 0.27. This limitation typically manifests when a subject exhibits unexpected head-tilt angles, extreme physical variations, or when the

background environment closely overlaps with the animal's boundary features.

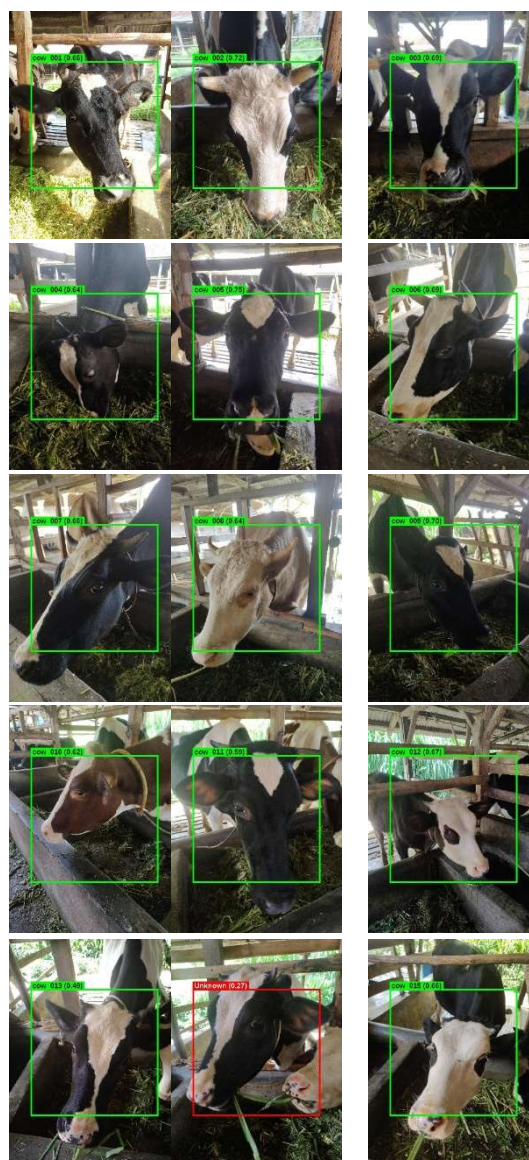


Figure 6. Test image result

Overall, the empirical evaluation demonstrates that the integrated computer vision model possesses strong generalization capabilities under complex barn environments, characterized by structural wooden obstructions, fluctuating ambient light, and irregular cow movements. The high identification accuracy underscores the practical feasibility of deploying this non-invasive system within a web-based livestock data management framework. To further minimize false negatives and improve individual discrimination thresholds, future research will focus on expanding the diversity of the local dataset repository and exploring deep learning architectures utilizing attention mechanisms to better handle complex background occlusions.

IV. CONCLUSION

This study successfully developed a dairy cattle facial recognition system based on a Convolutional Neural Network (CNN) as an alternative solution to conventional



livestock identification methods, which are invasive and may pose risks to animal welfare. Based on model testing using cattle facial images, the system was able to recognize individual cattle identities with a relatively high level of accuracy, indicating that the research objective of supporting digital and integrated livestock data management was achieved. The use of facial images as a biometric identity proved effective in reducing dependence on physical marking methods while minimizing the risk of data loss and damage in livestock record keeping.

Nevertheless, this study still has limitations, as testing was conducted using static image data with a limited dataset. Therefore, future research is recommended to increase both the size and diversity of the dataset, implement real-time testing in barn environments, and explore more varied model architectures or augmentation techniques to improve the system's accuracy and generalization capability under different image capture conditions.

should only answer the objectives of the research. Tells how your work advances the field from the present state of knowledge. Without clear Conclusions, reviewers and readers will find it difficult to judge the work, and whether or not it merits publication in the journal. Do not repeat the Abstract, or just list experimental results. Provide a clear scientific justification for your work, and indicate possible applications and extensions. This conclusion should be provided as a paragraph. You should also suggest future experiments and/or point out those that are underway.

REFERENCES

- [1] E. Tadele, D. Worku, D. Yigzaw, T. Muluneh, and A. Melese, "Precision of dairy farming: navigating challenges and seizing opportunities for sustainable dairy production in Africa," *Frontiers in Animal Science*, vol. 6, Mar. 2025, doi: 10.3389/fanim.2025.1541838.
- [2] S. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, "Big Data in Smart Farming – A review," *Agric. Syst.*, vol. 153, pp. 69–80, May 2017, doi: 10.1016/j.agsy.2017.01.023.
- [3] Z. Li *et al.*, "Dairy Cow Individual Identification System Based on Deep Learning," 2023, pp. 209–221. doi: 10.1007/978-981-99-0617-8_15.
- [4] S. Posam, L. K. Reddy G, and V. CM, "Automated dairy farm management system powered by IoT and ML," *Results in Engineering*, vol. 28, p. 107508, 2025, doi: <https://doi.org/10.1016/j.rineng.2025.107508>.
- [5] R. Mondal, S. Dan, S. Mandal, and S. Banik, "Animal identification: from traditional methods to Biometric approaches," *Journal of Livestock Science*, vol. 17, pp. 153–163, Mar. 2026, doi: 10.33259/JLivestSci.2026.153-163.
- [6] R. Nordquist, F. J. van der Staay, F. Eerdenburg, F. Velkers, L. Fijn, and S. Arndt, "Mutilating Procedures, Management Practices, and Housing Conditions That May Affect the Welfare of Farm Animals: Implications for Welfare Research," *Animals*, vol. 7, pp. 1–22, Feb. 2017, doi: 10.3390/ani7020012.
- [7] J. Liang, Z. Yuan, X. Luo, J. Qu, Y. Qi, and C. Wang, "Application of non-invasive monitoring technology in intensive sheep farming: A review," *Smart Agricultural Technology*, vol. 12, p. 101215, 2025, doi: <https://doi.org/10.1016/j.atech.2025.101215>.
- [8] J. Schillings, R. Bennett, and D. Rose, "Animal welfare and other ethical implications of Precision Livestock Farming technology," *CABI Agriculture and Bioscience*, vol. 2, May 2021, doi: 10.1186/s43170-021-00037-8.
- [9] S. Manteaw, B. Akpotosu, B. Folitse, and S. Mahama, "Assessing farm records-keeping behavior among small-scale pineapple farmers in the Nsawam Adoagyiri municipality, Ghana," *Ghana Journal of Agricultural Science*, vol. 56, pp. 34–45, Dec. 2021, doi: 10.4314/gjas.v56i2.4.
- [10] F. Oliveira, G. Ferraz, A. Guimarães André, L. Santana, T. Norton, and P. Ferraz, "Digital and Precision Technologies in Dairy Cattle Farming: A Bibliometric Analysis," *Animals*, vol. 14, p. 1832, Jun. 2024, doi: 10.3390/ani14121832.
- [11] H. Meng *et al.*, "Livestock Biometrics Identification Using Computer Vision Approaches: A Review," Jan. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/agriculture15010102.
- [12] T. T. Zin and P. Tin, "— Invited Review — Computer vision in precision livestock farming: artificial intelligence-driven technologies and applications for sustainable animal production," *Anim. Biosci.*, vol. 39, p. 260165, Apr. 2026, doi: 10.51713/ab.260165.
- [13] S. Zamroni *et al.*, "Sistemasi: Jurnal Sistem Informasi Identifikasi Moncong Sapi menggunakan Metode Jaringan Saraf Tiruan Konvolusional (CNN) Recognizing Cow Muzzle Patterns using the Convolution Neural Network (CNN) Algorithm." [Online]. Available: <http://sistemasi.ftik.unisi.ac.id>
- [14] E. Fiorilla, D. Vitturini, M. Bovo, M. Grangetto, and L. Ozella, "A computer vision framework for barn-wide monitoring of dairy cows in free-traffic systems with robotic milking," *Smart Agricultural Technology*, vol. 13, p. 101878, 2026, doi: <https://doi.org/10.1016/j.atech.2026.101878>.
- [15] S. Krishnan and S. S., "Cloud IOT based novel livestock monitoring and identification system using UID," *Sensor Review*, vol. 38, Dec. 2017, doi: 10.1108/SR-08-2017-0152.
- [16] G. BPS, "KECAMATAN KARANGPAWITAN DALAM ANGKA," 2020.
- [17] H. Meng *et al.*, "Livestock Biometrics Identification Using Computer Vision Approaches: A Review," Jan. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/agriculture15010102.
- [18] Y. Huang, "Deep Learning in Image Recognition," *Applied and Computational Engineering*, vol. 8, pp. 61–67, Aug. 2023, doi: 10.54254/2755-2721/8/20230082.



- [19] K. Djatnika, “ANALISIS PELAKSANAAN MANAJEMEN RISIKO DI INSTALASI FARMASI RUMAH SAKIT UMUM DAERAH TUGUREJO SEMARANG TAHUN 2018,” 2018.
- [20] M. El Sakka, J. Mothe, and M. Ivanovici, “Images and CNN applications in smart agriculture,” *Eur. J. Remote Sens.*, vol. 57, May 2024, doi: 10.1080/22797254.2024.2352386.
- [21] D. Marković, Z. Stamenković, B. Đorđević, and S. Randić, “Image Processing for Smart Agriculture Applications Using Cloud-Fog Computing,” *Sensors*, vol. 24, no. 18, Sep. 2024, doi: 10.3390/s24185965.
- [22] A. Khan *et al.*, “A survey of the vision transformers and their CNN-transformer based variants,” *Artif. Intell. Rev.*, vol. 56, pp. 2917–2970, Dec. 2023, doi: 10.1007/s10462-023-10595-0.

