

AI-Powered Cattle and Buffalo Breed Identification System Using Deep Learning for Smart Livestock Management

S Jadesha Gowda

dept. of Computer Science and Artificial Intelligence
Ballari Institute of Technology and Management
Ballari, Karnataka, India
Email: shivane Gowdrajadesha Gowda@gmail.com

T Dinesh Reddy

dept. of Computer Science and Artificial Intelligence,
Ballari Institute of Technology and Management
Ballari, Karnataka, India
Email: dineshreddy tiyyagura2005@gmail.com

Sharath Bhoopal B J

dept. of Computer Science and Artificial Intelligence
Ballari Institute of Technology and Management
Ballari, Karnataka, India
Email: sharathbhoopal785@gmail.com

Chanabasava. G

dept. of Computer Science and Artificial Intelligence
Ballari Institute of Technology and Management
Ballari, Karnataka, India
Email: Gchannabasava99@gmail.com

Anita Patil

dept. of Computer Science and Artificial Intelligence
Ballari Institute of Technology and Management
Ballari, Karnataka, India
Email: anitha.bijapur@gmail.com

Abstract:

India has one of the largest livestock populations globally, where cattle and buffaloes play a crucial role in dairy production and rural livelihoods. Accurate breed identification is essential for improving productivity, supporting breeding programs, and managing animal health. Traditional identification methods rely on expert observation and are often time-consuming and inconsistent. This paper presents a deep learning-based system for automatic cattle and buffalo breed classification using image data. The proposed model leverages transfer learning with convolutional neural networks to classify breeds such as Gir, Sahiwal, Ongole, Hallikar, Murrah, Jaffrabadi, Surti, and Mehsana. A web-based interface enables users to upload images and receive instant predictions along with record storage. The system provides a scalable and efficient solution for modern livestock management.

Keywords — Deep Learning, CNN, Transfer Learning, Livestock Classification, Smart Agriculture

I. INTRODUCTION

Livestock farming contributes significantly to the Indian economy, especially in rural areas where it supports income generation and agricultural activities. India is home to a wide variety of indigenous cattle and buffalo breeds, each with distinct characteristics and productivity levels. Identifying these breeds accurately is important for

selective breeding, disease management, and efficient farm planning. Conventional methods depend on visual inspection of physical features such as body structure, horn shape, and coat colour. These methods require expertise and may lead to inconsistent results when breeds share similar appearances or when crossbreeding occurs. Advances in artificial intelligence, particularly deep learning, have improved image recognition

capabilities. Convolutional Neural Networks (CNNs) can automatically learn distinguishing features from images and perform classification tasks effectively. This motivates the development of an automated system for livestock breed identification that reduces manual effort and improves reliability.

II. LITERATURE SURVEY

A. Singh et al. (2018) – Automated Recognition of Cattle Using Image Processing

Singh et al. presented one of the early approaches for cattle breed recognition using traditional image processing methods. The main objective of their study was to identify cattle breeds based on visible physical traits such as coat colour, texture patterns, and body appearance.

To achieve this, the researchers collected images of Indian cattle breeds and applied preprocessing steps before extracting handcrafted features such as colour histograms and texture descriptors. These features were then used in a rule-based classification model to identify breeds.

The study demonstrated that visual image features could support automatic cattle recognition and reduce dependency on manual observation. However, the system had several practical limitations. Its accuracy dropped significantly in poor lighting, and the results were highly sensitive to changes in camera angle and complex backgrounds. In addition, the model was limited to cattle breeds only and could not classify buffalo breeds. Due to slower processing and environmental sensitivity, it was not suitable for real-time farm deployment.

B. Ranjan and Verma (2019) – Cattle Identification Using Deep CNN

Ranjan and Verma proposed a cattle breed identification system using a Deep Convolutional Neural Network (CNN). The objective of their work was to improve breed recognition performance by replacing handcrafted features with automatically learned deep visual representations.

The authors trained the model using a dataset containing four Indian cattle breeds. Their CNN

architecture consisted of three convolutional layers followed by fully connected layers and a Softmax classifier. Data augmentation techniques such as image rotation and brightness adjustment were also applied to increase model robustness.

Experimental results showed that the CNN model performed better than traditional image-processing methods and achieved higher classification accuracy. However, the model required GPU resources for training and inference. Since the dataset size was relatively small, the system also showed overfitting issues when tested on unseen images. Another limitation was that the framework focused only on cattle breeds and did not include buffalo breeds. It was also not optimised for lightweight deployment.

C. Mehta et al. (2020) – YOLO Based Livestock Detection

Mehta et al. introduced a livestock monitoring framework using the YOLOv5 object detection model. Their main objective was to detect livestock animals in real-time farm images and video streams for surveillance and smart farming applications.

The researchers prepared annotated farm datasets and trained the YOLO model to identify the presence of animals in different scenes. Performance was evaluated using mean Average Precision (mAP) and detection speed metrics.

The study demonstrated strong real-time detection capability and faster processing compared to many earlier methods. It was especially useful for counting animals and monitoring movement in farms. However, the system focused only on detecting animals and did not classify their breeds. It also required high computational resources for optimal performance. Accuracy was reduced during night conditions, rain, or low visibility environments. In addition, the model depended on large annotated datasets for reliable training.

D. Patil and Pawar (2022) – Dairy Breed Classification Mobile App

Patil and Pawar proposed a mobile-based breed classification system aimed at helping farmers

identify dairy breeds through smartphones. The objective of the study was to make livestock recognition more accessible and practical for rural users.

In their framework, users captured animal images using a mobile application. The images were uploaded to a server where machine learning algorithms such as Support Vector Machine (SVM) and K-Nearest Neighbours (KNN) were used for classification. The final result was then sent back to the user.

The study highlighted the importance of mobile accessibility in agricultural applications. Farmers could use smartphones instead of depending on experts for breed identification. However, the system relied heavily on internet connectivity because all processing was performed on a remote server. Prediction speed was slower in low-network regions, which is common in rural areas. The application also supported only a small number of breeds and produced errors when side-angle images were captured.

E. Sharma et al. (2021) – VGG16 Based Cattle Image Recognition

Sharma et al. developed a cattle recognition model using the VGG16 deep learning architecture. The aim of their research was to improve breed identification by using a pre-trained neural network model. They trained the system with cattle image datasets after applying preprocessing and augmentation methods. The results showed improved recognition performance when compared with basic classification techniques. The study also proved that transfer learning can be useful for livestock image analysis. However, the model needed higher processing power and more training time because of its large network size.

Their goal was to improve breed identification through a pre-trained neural network. The model was trained using cattle images with preprocessing techniques. Results showed better accuracy than basic methods and confirmed the value of transfer learning. However, the system required more processing power and longer training time.

TABLE I
 Comparison of Literature Survey Papers

No.	Paper	Technique Used	Objective
1	Singh et al. (2018) [1]	Image Processing	Cattle breed recognition
2	Ranjan and Verma (2019) [2]	CNN	Classify cattle breeds
13	Mehta et al. (2020) [3]	YOLOv5	Real-time livestock detection
4	Patil and Pawar (2022) [4]	SVM + KNN Mobile App	Mobile breed identification

III. RESEARCH GAP

Existing systems address specific aspects of livestock identification but fail to provide a complete and practical solution. Traditional approaches lack scalability, while early automated methods are sensitive to environmental conditions. Deep learning models improve accuracy but often support limited breeds and require large datasets.

Furthermore, most systems focus only on cattle breeds and overlook buffalo breeds, which are equally important in dairy production. Many solutions also depend on internet connectivity and do not offer integrated data management features.

There is a need for a unified system that combines accurate classification, support for multiple breeds, efficient processing, and user-friendly deployment.

IV. PROPOSED FRAMEWORK

The proposed system integrates image preprocessing, deep learning, and web-based deployment into a single platform. Users can upload images through a mobile or web interface. The system processes the input image using techniques such as resizing, normalization, and noise reduction to enhance quality.

A pre-trained CNN model (such as MobileNetV2 or ResNet) is fine-tuned using transfer learning to classify livestock breeds. The model extracts key visual features and predicts the breed along with a confidence score.

The result is displayed instantly to the user, including breed name and prediction confidence. All records are stored in a database for future reference and analysis. This enables efficient data management and supports decision-making in livestock farming.

Expanding the dataset to include more breeds will improve generalisation. Offline mobile support can enhance usability in remote areas. Additional features such as disease detection and health monitoring can be integrated to create a comprehensive livestock management system.

VII. CONCLUSION

This work presents a deep learning-based approach for automatic cattle and buffalo breed identification. By combining transfer learning with image preprocessing and web deployment, the system provides accurate and efficient classification.

The proposed solution addresses the limitations of traditional methods and existing automated systems by offering scalability, accessibility, and practical usability. With further enhancements, it can play a significant role in improving livestock management and supporting the agricultural sector.

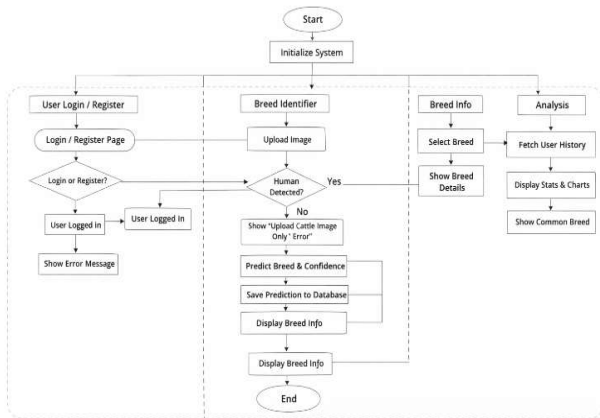


Fig. 1 Activity Diagram of Proposed System

V. APPLICATIONS

The system can be applied in various domains:

- **Dairy Farms:** Helps in breed identification for productivity planning and herd management.
- **Veterinary Services:** Assists in breed-specific diagnosis and treatment.
- **Livestock Markets:** Enables transparent transactions and breed verification.
- **Government Programs:** Supports livestock census and conservation initiatives.
- **Research Institutions:** Provides data for genetic and productivity studies.

VI. FUTURE WORK

Future improvements may focus on increasing model accuracy under challenging conditions such as low lighting and partial visibility. Advanced techniques like attention mechanisms and ensemble models can be explored.

REFERENCES

- [1] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in *Advances in Neural Information Processing Systems (NIPS)*, 2012, pp. 1097–1105
- [2] M. Sandler, A. Howard, M. Zhu, A. Zhmoginov, and L. Chen, "MobileNetV2: Inverted Residuals and Linear Bottlenecks," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2018, pp. 4510–4520.
- [3] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," *arXiv preprint arXiv:1804.02767*, 2018
- [4] K. He, X. Zhang, S. Ren, and J. Sun, "Deep Residual Learning for Image Recognition," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016, pp. 770–778.
- [5] T. Chen and C. Guestrin, "XGBoost: A Scalable Tree Boosting System," in *Proc. ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining*, 2016, pp. 785–794.
- [6] TensorFlow Developers, "TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems," Google, 2023. [Online]. Available: <https://www.tensorflow.org>
- [7] Indian Council of Agricultural Research (ICAR), "Breed Descriptors of Indigenous Cattle and Buffalo Breeds of India," New Delhi, India.
- [8] K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," *arXiv preprint arXiv:1409.1556*, 2014.
- [9] M. Tan and Q. Le, "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks," in *Proc. International Conference on Machine Learning (ICML)*, 2019, pp. 6105–6114.
- [10] S. Ren, K. He, R. Girshick, and J. Sun, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks," in *Advances in Neural Information Processing Systems (NIPS)*, 2015, pp. 91–99.
- [11] F. Chollet, "Xception: Deep Learning with Depthwise Separable Convolutions," in *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2017, pp. 1251–1258.
- [12] A. Howard et al., "Searching for MobileNetV3," in *Proc. IEEE/CVF International Conference on Computer Vision (ICCV)*, 2019, pp. 1314–1324.

- [13] G. Huang, Z. Liu, L. Van Der Maaten, and K. Weinberger, "Densely Connected Convolutional Networks," in Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR), 2017, pp. 4700–4708.
- [14] D. P. Kingma and J. Ba, "Adam: A Method for Stochastic Optimization," arXiv preprint arXiv:1412.6980, 2014.
- [15] F. Pedregosa et al., "Scikit-learn: Machine Learning in Python," Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.