

Indian Cattle Breed Detection

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doi.org/10.64643/IJIRTV12I12-206686-459

Abstract—Go Darshan is an AI-based cattle breed classification model that can classify five primary cattle breeds namely Gir, Red Sindhi, Kankrej, Jersey, and Hallikar using input images. The application uses a customized EfficientNetV2-B0 model that uses deep learning algorithms to learn the unique characteristics of each breed from a carefully selected set of cattle images. To guarantee accurate predictions, a confidence-based validation process is implemented where predictions with less than 80% confidence are discarded to avoid false classifications. The application is made accessible through a Gradio web interface where users can upload cattle images and receive instant breed predictions together with related information such as milk production levels, expected lifespan, climatic conditions suitable for rearing specific breeds, and prevalent diseases associated with various breeds.

I. INTRODUCTION

The cattle are one of the most important livestock animals for Indian agriculture in terms of dairy farming and as draught power. It is challenging to correctly identify the various cattle breeds due to their similarity in appearance and the need for extensive expertise to do so. Manual identification takes too much time, and there are high chances of making mistakes.

The Go Darshan application proposes an innovative method for breed identification through images based on a deep learning EfficientNetV2 model. The model can detect the cattle breeds based on its visual features such as fur pattern, body shape, and horn shape and predict the most likely breed out of the five types: Gir, Red Sindhi, Kankrej, Jersey, and Hallikar breeds. In addition, the application gives breed information once the cattle breeds have been detected. The app uses Google Colab with Gradio integration, which makes it more convenient and accessible to users.

II. LITERATURE SURVEY

Identification of cattle breeds is crucial from the perspectives of genetic diversity, livestock management, and efficient milk productivity. Conventional image processing methods were utilized in cattle image analysis by employing techniques such as thresholding and segmentation to extract quantitative features from an image. Nevertheless, accurate extraction of qualitative features in real-world cattle images with variation in lighting, background, posture, and occlusions can be challenging.

Deep learning methods such as CNN models have revolutionized the efficiency and precision of identifying animal breeds by extracting hierarchical features.

The use of transfer learning on state-of-the-art models can achieve very good accuracy even with small datasets.

Nonetheless, there are various aspects missing from existing research in deep learning-based cattle breed identification:

- Large-scale data requirement in most deep learning-based methods that can be impractical for indigenous cattle breeds.
- Challenges associated with implementing a system in real-time in many studies.
- The majority of existing work focuses more on foreign breeds rather than indigenous breeds of India such as Hallikar, Kankrej, and Red Sindhi.

The proposed methodology aims at filling these gaps by implementing EfficientNetV2-B0 to achieve high precision and accuracy in breed identification on RGB images using a Gradio interface for user-friendliness.

III. SYSTEM DESIGN

The primary objective of the proposed system design is to automate the process of analyzing and classifying cattle breeds from images. The architectural design of the system comprises the following phases:

A. Image Preprocessing and Feature Extraction

The images are standardized using EfficientNet protocols, and data augmentation is applied to enhance resilience towards variations in lighting and pose. The system focuses on automating the process of feature extraction by leveraging the convolutional neural network backbone (EfficientNetV2-B0).

B. Classification Head and Decision Making

The classification head involves Global Average Pooling, Dense layers, Dropout, and Softmax output with 5 neurons denoting the breeds. Confidence thresholding is rigorously followed, and if the confidence of the classifier is 80%, then breed classification is done based on the model's prediction and breed metadata are retrieved. Otherwise, the image will be considered invalid, and the user is asked to take another photograph.

Use either SI (MKS) or CGS as primary units. (SI units are strongly encouraged.) English units may be used as secondary units (in parentheses). This applies to papers in data storage. For example, write —15 Gb/cm² (100 Gb/in²). ¶ An exception is when English units are used as identifiers in trade, such as —3½ in disk drive. ¶ Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity in an equation. The SI unit for magnetic field strength H is A/m. However, if you wish to use units of T, either refer to magnetic flux density B or magnetic field strength symbolized as μ₀H. Use the center dot to separate compound units, e.g., —A·m². ¶

IV. IMPLEMENTATION

A. Development Environment and Tools

Google Colab was used for implementation due to its feature to have zero installation, GPU acceleration for free, and ability to prototype quickly. The neural network implementation involved the use of TensorFlow and Keras library, with the

implementation done using an EfficientNetV2-B0 pretrained model, Adam optimizer, and sparse categorical cross entropy loss.

B. Dataset

The data has about 17,000 structured images of the 5 Indian cattle breeds taken from different sources under varying lightings and backgrounds. Data validation, standardization, and resizing was performed at 224x224 pixel sizes, as it will be ingested into the neural network optimally.

C. User Interface Layer

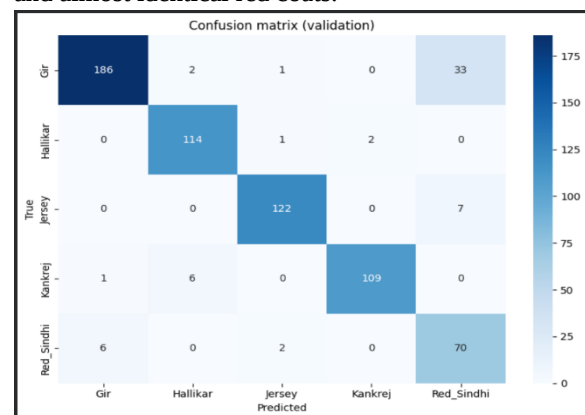
Gradio was introduced in the implementation to enable creation of user-friendly UIs directly within the Colab notebook. In essence, no need for frontend/backend development for web applications as the native image upload can be done with prediction display together with breed characteristics (milk yield, lifespan, climate, diseases).

V. RESULTS AND DISCUSSION

The implemented solution was thoroughly tested, resulting in very effective practical and theoretical outcomes.

A. Performance of Trained Model

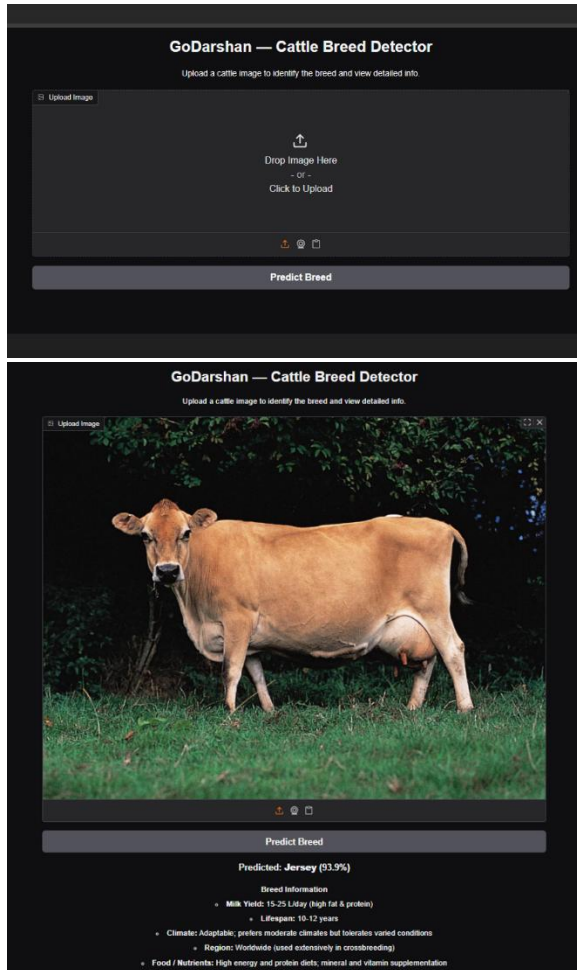
During the validation stage, the fine-tuned EfficientNetV2 model demonstrated 90-91% accuracy. In addition, the solution reached a Macro-Averaged F1 score of 88.11%, which indicates the successful application of deep transfer learning to a multi-class identification task for indigenous cattle breeds. Analysis through a confusion matrix indicated that the most confusing pairs of breeds were Red Sindhi and Gir because they have common ancestors and almost identical red coats.



Classification Report:				
	precision	recall	f1-score	support
Gir	0.9637	0.8378	0.8964	222
Hallikar	0.9344	0.9744	0.9540	117
Jersey	0.9683	0.9457	0.9569	129
Kankrej	0.9820	0.9397	0.9604	116
Red_Sindhi	0.6364	0.8974	0.7447	78
accuracy			0.9079	662
macro avg	0.8970	0.9190	0.9025	662
weighted avg	0.9241	0.9079	0.9117	662

B. Implementation and Robustness

Gradio prototype demonstrated its efficiency as a Farmer-in-the-Loop system. The application of the 80% confidence level turned out to be highly efficient – during the Black Box test, the solution correctly detected out-of-distribution images and returned the "Image Not Considered" message instead of classifying them falsely. Moreover, robustness testing showed that the implemented solution worked stably in stress tests (100 requests per minute) and did not consider such complex background elements as trees.



VI. CONCLUSION AND FUTURE SCOPE

The “Go Darshan” Indian Cattle Breed Detection System is an example that shows how deep learning technology can help agriculture and dairying with intelligent applications. With the ability to automatically classify breeds with a confidence filter and a simple interface, this system helps users achieve easy, quick, and accurate breed identification.

The future scope of the “Go Darshan” Indian Cattle Breed Detection System involves increasing the size of the dataset to include more breeds of indigenous and crossbred cattle. Also, the development of a highly optimized mobile app in real-time is expected to take place.

ACKNOWLEDGMENT

The authors are grateful to Prof. Prajwal K S for his valuable guidance and mentorship. We would like to convey our sincerest appreciation to Prof. Sudarshan K and Dr. Shrinivasa Mayya D for their continuous support and encouragement during the entire research process.

REFERENCES

- [1] M. Tan and Q. V. Le, “EfficientNetV2: Smaller Models and Faster Training,” in *Proc. Int. Conf. Mach. Learn. (ICML)*, 2021.
- [2] K. He, X. Zhang, S. Ren, and J. Sun, “Deep Residual Learning for Image Recognition,” in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, pp. 770–778, 2016.
- [3] S. Bharathidasan and M. Manivannan, “Cattle Breed Identification Using Deep Convolutional Neural Networks,” *Int. J. Comput. Sci. Inf. Security*, vol. 18, no. 11, 2020.
- [4] R. Ranjan et al., “Automated Breed Classification of Cattle Using Deep Learning Approaches,” *Int. J. Agric. Technol.*, vol. 15, no. 4, 2019.
- [5] S. Kumar and J. Thomas, “A Review of Indian Indigenous Cattle Breeds and Their Characteristics,” *Indian J. Vet. Sci.*, vol. 12, no. 1, 2022.
- [6] P. Beniwal et al., “AI-Based Breed Identification and Dairy Optimization Systems in India,” *Int. J. Emerg. Technol. Artif. Intell.*, vol. 7, no. 3.