International Journal of Advances in Engineering and Management (IJAEM)
Volume 8, Issue 2 Feb. 2026, pp: 263-266 www.ijaem.net ISSN: 2395-5252

Deep Learning–Driven Image-Based Breed Identification for Cattle and Buffalo

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Date of Submission: 12-02-2026 Date of Acceptance: 23-02-2026

Abstract - This study represents a progress paper as it documents the ongoing development of an image-based cattle and buffalo breed recognition system built upon deep learning techniques. Unlike a traditional review, it extends prior published work by focusing on practical aspects such as dataset preparation, systematic preprocessing, model implementation using MobileNetV2, and the training strategies employed, while also highlighting intermediate observations throughout the process. The central objective is to design a computationally efficient and scalable framework that can be realistically deployed in farm environments for real-time breed identification. Early experimental outcomes demonstrate encouraging convergence trends, reinforcing the effectiveness of transfer learning in addressing the challenges of livestock classification, particularly when working with limited datasets. These findings not only validate the feasibility of the approach but also lay the groundwork for future refinements that could further enhance accuracy, robustness, and applicability in real-world agricultural settings.

Key Words: Cattle Breed Recognition, Buffalo Identification, MobileNetV2, CNN, Deep Learning.

I. Introduction

This paper aims to examine the article authored by Eikenberry et al. (2018), which addresses the key concern concerning marijuana use in elderly adults.<|human|>Introduction: This essay will discuss the preparation, systematic preprocessing, model implementation using MobileNetV2, and the training strategies employed, while also highlighting intermediate observations throughout the process. The central objective is to design a computationally efficient article by Eikenberry et al. (2018) that touches upon the most important issue related to marijuana use among the elderly population. Precision Agriculture, dairy management, genetic improvement and disease monitoring are some of the areas where automated livestock breed identification is important. Physical identification which involves identifying by use of physical characteristics is subjective and not reliable in actual farm conditions. The paper is a progress report that records the shift in the theoretical analysis towards the practical implementation of a MobileNetV2-based breed recognition system.

The proposed progress research study is aimed at implementing an image-based cattle and buffalo breed recognition system based on a deep learning framework and evaluating it. Fig. X shows the system workflow in which the input images are processed step by step to automatically predict the breed of the image. It starts with the acquisition of the image of cattle and buffalo taken in the natural farm conditions. These images are the input in the system and they represent variations in pose, lighting, and background. Image resizing, image normalization and noise removal are preprocessing functions which are used to make sure that the deep learning model is compatible with each image. This will enhance the consistency of the data and aid in the training of models. After preprocessing, the system focuses on the areas of the animal that are of interest in order to enhance the system to learn features and reduce the effects of the background.

The resulting processed image is sent to the deep learning model where the hierarchical features of the image of the form of texture, shape, and coat patterns are extracted by convolutional layers. The use of pooling layers helps to decrease the dimension of features and reduce the amount of computations but still maintain discriminative information. An average pooling layer worldwide further narrows down the extracted features making learning and minimizing the chances of overfitting highly efficient. These characteristics are forwarded to a fully connected layer which is learned to give the relationship between the extracted features and the breed categories. Lastly, the output layer gives breed predictions using probability scores. Model

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training and validation is being done at the current research stage. At an initial stage, there is evidence of successful feature learning and characterized convergence behavior. Further development will be placed on quantitative performance assessment, data set growth and real- time implementation on resource limited devices.

II. Review Methodology

The review methodology adopted in this study aims to systematically analyze and synthesize existing research related to cattle and buffalo breed recognition using image-based and deep learning approaches. The methodology is designed to ensure comprehensive coverage, relevance, and critical evaluation of the selected literature.

Initially, a structured literature search was conducted using reputable digital libraries such as IEEE Xplore, SpringerLink, ScienceDirect, Elsevier, Google Scholar, and MDPI. Keywords including *cattle breed recognition*, *buffalo identification*, *deep learning in livestock*, *convolutional neural networks*, *MobileNet*, *biometric animal identification*, and *precision agriculture* were used to retrieve relevant publications.

The collected studies were filtered based on predefined inclusion criteria. Only peer-reviewed journal articles, conference papers, and recent survey papers published within the last decade were considered. Studies focusing on traditional manual identification methods or unrelated animal species were excluded to maintain domain relevance.

Selected papers were then categorized according to their methodological approach, such as conventional image processing techniques, convolutional neural networks, lightweight deep learning architectures, biometric-based identification (e.g., muzzle patterns), multi-view and hybrid models, and transformer-based approaches. Each category was analyzed with respect to dataset size, model architecture, feature extraction techniques, performance metrics, and deployment feasibility.

A comparative analysis was performed to identify strengths, limitations, and research trends across the reviewed studies. Particular emphasis was placed on real-time applicability, computational efficiency, robustness under uncontrolled farm conditions, and scalability to large datasets. Research gaps related to dataset standardization, mobile and IoT deployment, and model explainability were also identified.

Finally, insights derived from the review were used to define the motivation and direction of the proposed progress research, guiding the selection of model architecture and system design for practical livestock breed recognition.

III. PROPOSED METHODOLOGY

The proposed methodology is designed to implement an efficient and scalable cattle and buffalo breed recognition system using the MobileNetV2 architecture. The workflow consists of dataset collection, preprocessing, augmentation, feature extraction, training strategy, and evaluation metrics, as illustrated in Fig. 1.

A. Dataset Collection

Images are collected from farms, repositories, and field datasets, ensuring natural variations in pose, lighting, and background.

B. Preprocessing

All images are resized to 224×224 pixels, normalized, and subjected to noise reduction to ensure consistency and improve model convergence.

C. Data Augmentation

To overcome dataset limitations, augmentation techniques such as rotation, zoom, brightness adjustment, flipping, shifting, and shearing are applied. This increases dataset diversity and improves generalization.

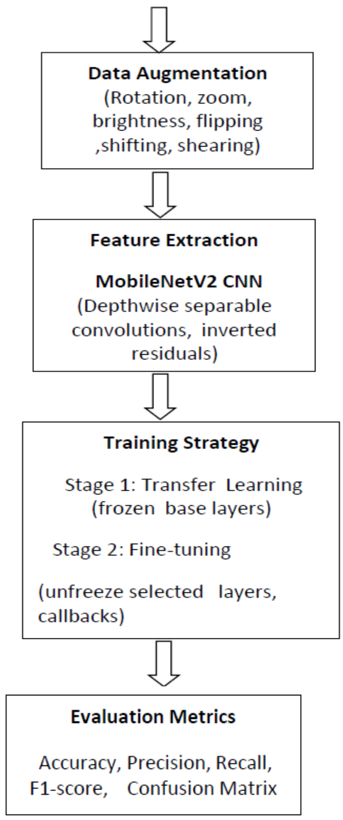

Fig. 1- Proposed Workflow for cattle and Buffalo Breed Recognition using MobileNetV2.

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IV. Training Strategy

The model training process is carried out in two structured phases to ensure stable convergence and effective feature adaptation. In the first phase, a transfer learning approach is adopted where the pre- trained backbone network is utilized with its convolutional base layers kept frozen. This allows the model to leverage previously learned visual representations while training only the newly added classification layers on the target cattle and buffalo dataset. Freezing the base layers helps preserve general image features and prevents overfitting during the initial training stage.

In the second phase, selective fine-tuning is performed by gradually unfreezing the upper layers of the backbone network. This enables the model to adapt higher-level feature representations specifically to breed-related characteristics such as texture patterns, body structure, and color variations. Fine-tuning improves model generalization while maintaining computational efficiency.

To enhance training stability and prevent performance degradation, optimization strategies such as early stopping and adaptive learning rate scheduling are incorporated. Early stopping monitors validation performance and halts training when no further improvement is observed, reducing overfitting risk. Learning rate scheduling dynamically adjusts the step size during training, facilitating smoother convergence and improved accuracy.

V.Expected Results

The working of the proposed cattle and buffalo breed recognition system follows a sequential deep learning pipeline, as illustrated in Fig. X. The system processes an input image and performs automated breed prediction using a convolutional neural network.

1. Input Image Acquisition

The process begins with capturing an input image of a cattle or buffalo. The image may be obtained from farm environments, mobile devices, or existing image datasets. These images typically include variations in pose, lighting, and background, reflecting real-world farm conditions.

2. Image Preprocessing

Before feeding the image into the deep learning model, preprocessing operations are applied to enhance data consistency and model performance. This includes resizing the image to a fixed resolution, normalization of pixel values, and noise reduction.

Preprocessing ensures uniform input and improves convergence during training.

3. Region of Interest (ROI) / Feature Extraction Preparation

In this stage, the relevant region of the animal (such as the body, face, or head area) is emphasized. This step helps the model focus on discriminative visual characteristics related to breed identity while reducing background influence.

4. Convolutional Layers

The preprocessed image is passed through multiple convolutional layers of the deep learning model.

These layers automatically extract low-level and high-level features such as edges, textures, coat patterns, and structural details that are crucial for breed differentiation.

5. Pooling Layers

Pooling layers are applied after convolutional layers to reduce the spatial dimensions of feature maps.

This operation decreases computational complexity while retaining the most important features, improving robustness to minor variations in image position and scale.

6. Global Average Pooling

Global Average Pooling condenses each feature map into a single representative value. This reduces the number of parameters compared to traditional fully connected layers and helps prevent overfitting, making the model suitable for lightweight and real-time deployment.

7. Fully Connected Layer

The extracted features are then passed to a fully connected layer, which learns complex relationships between features and breed classes. This layer acts as a classifier by combining the learned feature representations.

8. Breed Prediction

Finally, the output layer generates the predicted breed of the cattle or buffalo using a softmax activation function. The class with the highe st probability selecteas the final breed
prediction.

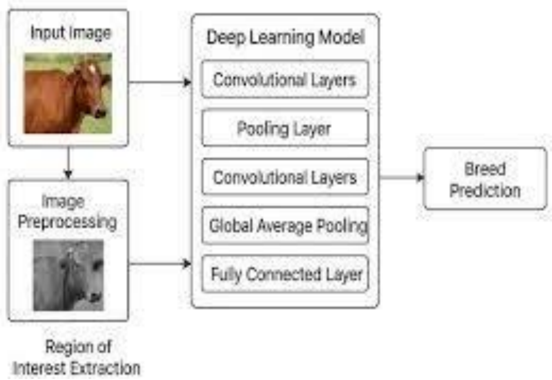

Chart -1: Breed Prediction chart

VI.CONCLUSIONS

This progress paper demonstrates the transition from a comprehensive literature review to the practical development of an image-based cattle and buffalo breed recognition system using deep learning. The study confirms that convolutional neural networks provide a reliable foundation for automating breed identification, particularly under realistic farm conditions. In line with earlier findings, lightweight architectures such as MobileNetV2 are shown to be well suited for this task due to their low computational complexity and ability to perform effectively on limited datasets, making them appropriate for real-time and edge-based deployment.

The ongoing implementation highlights the advantages of data augmentation, transfer learning, and fine- tuning strategies in improving model stability and feature learning. While biometric and multi-view approaches reported in prior studies offer high accuracy, the current progress focuses on achieving a balance between accuracy, scalability, and deployability in uncontrolled environments. Initial observations indicate that the proposed framework is capable of learning discriminative breed-specific features, even in the presence of variations in pose, lighting, and background.

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