Ensemble Learning Algorithm for Cattle Breed Identification using Computer Vision Techniques

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Abstract. This research paper introduces a robust ensemble learning algorithm tailored for cattle breed identification, making use of the integration of cutting-edge computer vision techniques. The methodology combines Convolutional Neural Networks (CNN), YOLO object detection, canny edge detection, k-means image segmentation, and greyscale imaging to overcome inherent limitations in existing methodologies. Addressing challenges associated with obscured features and the presence of dirt on cows, the framework ensures precise and accurate breed prediction. The algorithm adopts a pipeline, encompassing critical stages such as cow identification, optimized resizing, k-means image segmentation, greyscale conversion, and canny edge detection. Through the union of these techniques, the ensemble learner, employing a voting-based mechanism, achieves outstanding performance in the classification of cattle breeds. This research contributes to the advancement of state-of-the-art methodologies for cattle breed identification, providing a foundation for improved decision-making processes in agricultural and livestock management.

Keywords: Cattle Breed Identification, Ensemble Learning, Image Segmentation, CNN

1 Introduction

Cattle have played a pivotal role in shaping human civilization, with their domestication being a key indicator of socio-economic status in agrarian societies like India. Over the past 8000 years, cattle have adapted to diverse geographic conditions and various breeding purposes, including meat production, dairy products, draught, hides, and religious practices **[1]**. The evolving trends of health consciousness, selective consumption behaviour, and the cultural significance of traditional breeds emphasize the need for the conservation of indigenous cattle breeds. In contemporary times, cattle breeds are categorized into intraspecific groups with distinct features, and crossbreeds have gained popularity. Dairy farming, a common sector for income generation, relies on cattle with similar physical characteristics such as colour, horns, body type, and performance. However, the substantial and seemingly arbitrary variations in

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appearance and performance make it challenging for individuals to consistently classify cattle breeds. The conservation of locally adaptable breeds is crucial for regional economic development through enhanced agriculture productivity. Various studies have highlighted the potential of leveraging the unique characteristics of numerous cattle breeds for effective livestock management. Computer vision techniques have emerged as a promising solution in recent decades **[2],[3],[4]**. The increasing applications of Artificial Intelligence (AI) have motivated researchers to explore its scope in addressing real-world problems, including prediction, classification, identification, and analysis. The development of AI models for computer-assisted cattle identification, classification, and scoring holds great promise in validating traditional inferences for the benefit of the broader community.

2 Related Work

Prior studies have significantly contributed to the field of cattle breed identification, employing various methodologies rooted in computer vision. Manoj et al. utilized image datasets for categorizing cattle breeds, incorporating diverse perspectives, and employing SIFT for feature extraction **[5]**. Convolutional Neural Networks (CNNs) proved effective in discerning both facial and body characteristics of cows. Mahmud et al. underscored the historical efficiency of deep learning in monitoring cattle health, emphasizing real-time tracking and health assessment **[6]**. The study featured the application of deep learning models such as ResNet, DenseNet, VGGNet, Inception V3, and MobileNet. Similarly, Andrew et al. automated Holstein Friesian cow recognition using computer vision pipelines and deep neural architectures, with R-CNN aiding cattle detection and localization **[7]**. Bezsonov et al. introduced a pre-trained Mask-RCNN convolutional neural network for animal detection and breed identification, utilizing the SGD algorithm for enhanced training **[8]**. Ráduly et al. explored dog breed identification, employing NASNet and Inception-ResNet-V2 architectures on the Stanford dogs dataset, demonstrating potential applications in cattle breed identification **[9]**. Ayanzadeh et al. emphasized the importance of fine-tuning and data augmentation in dog breed identification, evaluating ResNet, DenseNet, and GoogleNet on the Stanford dog breeds dataset **[10]**.

Dutta extended the application to sheep breed classification, utilizing Convolutional Neural Network algorithms with a focus on facial features **[11]**. Jwade et al. implemented VGG-16 for classifying sheep breeds, achieving notable accuracy through fine-tuning **[12]**. Rahman et al. ventured into pigeon breed identification, employing CNN-based architecture and transfer learning **[13]**. The study compared various models, with Xception exhibiting superior performance. Ahmad et al. innovatively utilized a YOLO object detection model for animal muzzle point extraction, showcasing impressive mean average precision **[14]**. Zheng et al. addressed challenges in cow individual identification and tracking, developing YOLO-BYTE with a Self-awareness and Convolution combined module (ACmix) **[15]**. Mahmud et al.'s comprehensive analysis acknowledged recent advancements in deep learning applications for cattle identification and health monitoring **[16]**. Face identification models have also gained prominence, with Yao et al. proposing the use of Faster R-CNN and RetinaFace for robust cow face detection **[17][18][19]**. Qiao et al. integrated CNN and LSTM for cattle identification using video data, while Xu et al. enhanced feature extraction through C-LBP and self-attention modules **[20][21]**. The research work done in the field has been conducted primarily on industrial grade cattle imagery and has not been tailored for Indian breeds. But, this collective body of research sets the stage for our proposed ensemble learning algorithm, which amalgamates various computer vision techniques for accurate and efficient cattle breed classification.

3 Research Methodology

Figure 1 shows the methodology (pipeline) undertaken and proposed during the research study. The process involves taking an image and identifying the cow through YOLOv7, followed by cropping to the area of focus. Then the next steps involved are, performing 3 different pre-processing techniques on the image, grey scaling, k-means image segmentation and canny edge detection. The 3 new images, along with the original image are then fed into individually trained CNN models, and the resultant predictions are processed by a voting ensemble learner, to provide the final predicted breed.

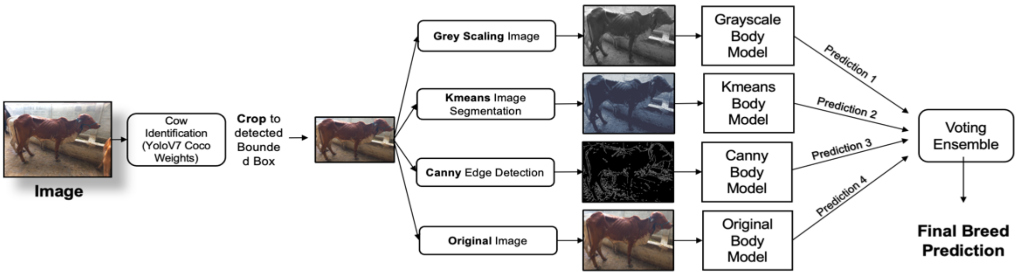


Fig. 1. Cattle Breed Detection Pipeline

3.1 Cow Identification (YOLO - COCO Weights)

In the initial stage of the pipeline, the YOLO (You Only Look Once) algorithm, employing COCO (Common Objects in Context) pre-trained weights, is utilized to identify cows within the images. YOLO, functioning as an object detection algorithm, exhibits the capability to detect multiple objects in an image. Through the incorporation of pre-trained COCO weights, the algorithm accurately discerns cows in the provided images. The YOLO algorithm furnishes bounding box coordinates, class labels, and p values for identified objects, all subject to a predetermined confidence level, 0.25 for our study.

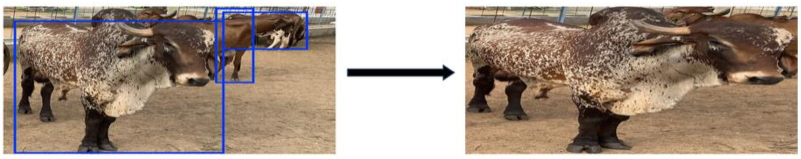


Fig. 2. YoloV7 based Cow Detection and resizing

Cropping Image to Identified Cow Body. Following the identification of cows within the images (class 19 in the COCO dataset represents cows), the subsequent step involves cropping the images to isolate the cow's body. This process entails extracting bounding box coordinates derived from the YOLO algorithm and subsequently cropping the image accordingly. The objective is to eliminate extraneous information, focusing exclusively on the region of interest. The cow with the highest p value and confidence, among multiple identified cows, is selected and cropped for further analysis. **Figure 2** illustrates a scenario with multiple cows in the frame; the cow with the highest p value and confidence is singled out and subjected to cropping. To standardize the dimensions of the cow images for subsequent processing, the cropped cow body images are resized to 500x500 pixels. This resizing operation ensures that all images undergo analysis at uniform dimensions, facilitating accurate comparison and classification.

3.2 Image Pre-processing

a) Grey scaling **b)** K Means Image Segmentation **c)** Canny Edge Detection

Fig. 3. Image Pre-Processing on Cow Body

Gray Scaling. The greyscale conversion of the cropped and resized cow body image is the subsequent step. This process involves transforming coloured images to greyscale images by adjusting the RGB colour intensity of each pixel, as illustrated in **Figure 3b.**

K-means Image Segmentation. The cropped and resized cow body image undergoes K-means-based image segmentation in this step. The K-means clustering algorithm is employed to group pixels with similar characteristics. A selected k value of 5 determines the number of clusters for body segmentation. A higher k value yields a more distinct but potentially biased image, while a lower k value may overlook crucial features. Figure 4 illustrates the K-means Image Segmentation of the cow's body. **Figure 3b** showcases the segmentation of the cow's body through K-means clustering.

Canny Edge Detection. The subsequent step involves the application of canny edge detection to outline the boundaries of the cow's body. The canny edge operator, a multi-stage algorithm, employs a 5x5 Gaussian filter for image smoothing, gradient magnitude thresholding for eliminating spurious responses, double thresholding, and a higher cut-off bound for identifying potential edges. The final output comprises strong connected edges, representing the delineation of the cow's body boundaries, as depicted in **Figure 3c**.

3.3 Ensemble Learning Base Model Architecture

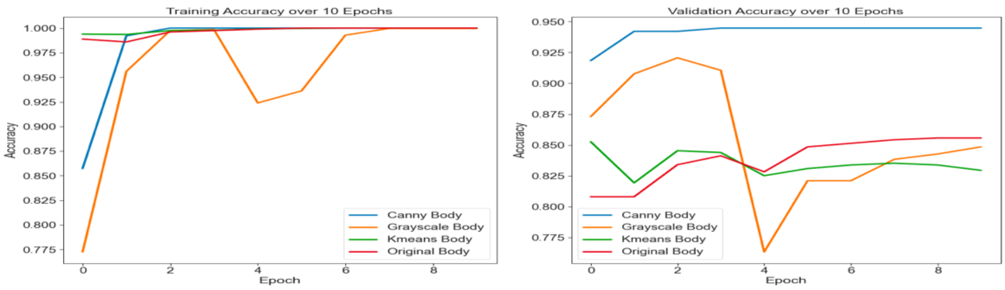
To improve the accuracy and robustness of cattle breed identification, an ensemble learning approach is employed in this study. The ensemble learning framework combines the predictions of multiple base models, each trained on a different subset of the pre-processed dataset. The goal is to leverage the diversity of the individual models to obtain a more accurate and reliable prediction. The ensemble learning framework consists of a base Convolutional Neural Network

(CNN) architecture, with an input shape of (500,500). The architecture consists of three convolutional layers with max pooling, followed by flattening and two dense layers. The model comprises a total of 60,026,570 parameters, including trainable parameters, with the last dense layer producing a 3-class output, for the three breeds present. These base models are trained independently on their respective pre-processed datasets.

3.4. Model Training

Each base model is trained using the Adam optimizer with a Sparse Categorical Cross entropy loss function. The training process involves iterating over the training dataset for 10 epochs. The training and validation dataset included 3404 cow body images and 2729 cow face images of three different breeds. The classes were imbalanced in nature, with the Sindh Cow breed consisting of only 18% of the dataset. A training validation split of 80:20 is used. During training, the models extract relevant features from the images and make predictions based on those features. Post training the validation split is used for validating the predictions of the models.

4 Results and Model Evaluation

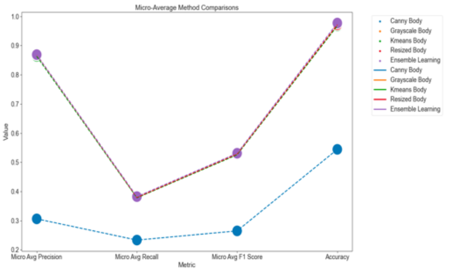


a) Training Accuracy **b)** Validation Accuracy

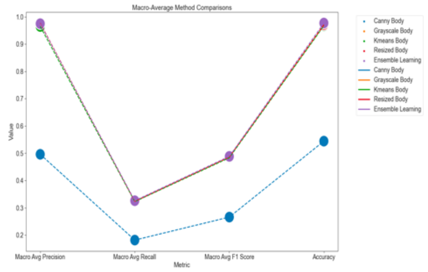
Fig. 4. Accuracy over 10 iterations (epochs)

As evident in Figure 4a, the accuracy results demonstrate consistently high performance across iterations. The canny model, greyscale and k means models achieved 0.857 to 1.0, 0.773 to 1.0 and 0.994 to 1.0 accuracies over 10 epochs respectively. It is easy to assume, regardless of the processing technique, all models effectively identified cow breeds based on body features. But upon closer examination, the validation accuracy (Figure 4b), is around 85 percentage for all the models, barring canny edge detection, indication biasness.

To evaluate the performance of the ensemble learner, a separate validation dataset is used. In the evaluation of a classification model, precision, recall, and F1 score are commonly used metrics to assess its performance. These metrics provide insights into the model's ability to correctly identify positive instances (precision) and capture all positive instances (recall), while the F1 score represents a balance between the two. The final accuracy is compared with both micro and macro evaluation metrics (**Figure 5a** and **Figure 5b**). Micro average metrics considers the overall precision and recall across all classes, while macro average metrics provides an equal weightage to each class.



a) Micro-Average



b) Macro Average

Fig. 5. Model-wise Micro and Macro Evaluation Metrics Comparison

Analysing the micro and macro average scores of precisions, recall, and F1 score, it is evident that the ensemble learning approach outperforms the other methods. The ensemble learning technique achieves a high micro average precision of 0.869 and the highest f1 score and macro average precisions amongst all models indicating a low rate of false positive classifications, as evident in **Figure 6**. The canny edge model predicted too many false positives for Gir breed, but that didn't impact the overall predictions from the ensemble learner. It is important to note that the dataset used is of distorted images clicked by farmers, from local farmlands, and on low-resolution mobile phones, henceforth the modest evaluation metrics.

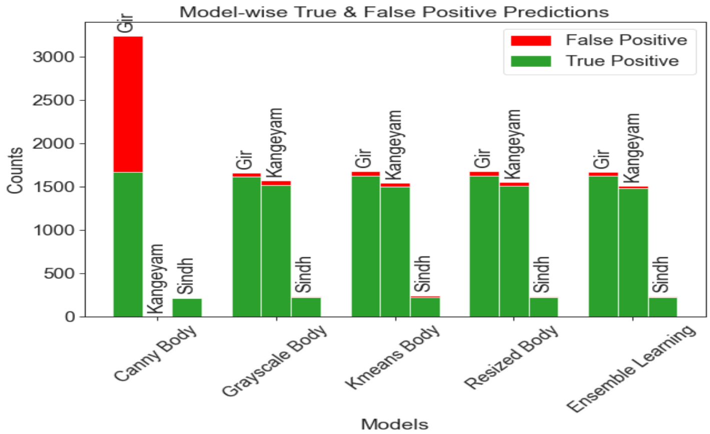


Fig. 6 Model Prediction Analysis (True vs False Positive)

4 Conclusion

The ensemble learning framework introduced in this study combines the predictions of multiple base CNN models to improve the accuracy and reliability of cattle breed identification. By leveraging advanced computer vision techniques and the diversity of individual models, the ensemble approach overcomes the limitations of existing methodologies. Although the differences between models (figure 5) might be visually minute, the overall generalization, precision and accuracy (figure 6) of the ensemble learner is significantly higher. The comparison of different models and their performance metrics demonstrates the effectiveness of the ensemble learner. The proposed framework serves as a valuable tool for enhancing agricultural and livestock management practices, with wide-ranging implications in the field.

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