MooNet: A Lightweight CNN For Mobile Cattle Breed Recognition With QR-Based Digital Traceability

Mr. Uttam Tiwari[1], Ms. Neha Kumari[2]
[1,2]*B.Tech. CSE Student, Dr. A.P.J Abdul Kalam Institute of Technology, Tanakpur*
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***Abstract*—The correct identification of cattle breeds is a factor related to livestock management, genetic assessment, and the maintenance of trustworthy electronic data. Practically, non-expert operators tend to mislabel morphologically similar indigenous and crossbred animals where images are taken at varying lighting, motion blur, occlusions and with a crowded farm background. This compromises the quality of big livestock databases. This paper introduces MooNet, a mobile and edge-delivered convolutional neural network that is based on MobileNetV4 and capable of recognizing cattle by their breed in real-time. The 12,000 annotated images used to train MooNet are field-based data as they have inherent variation of the viewpoint, light, and image complexity. The model performs at 96.45% accuracy, 96.47% precision, 96.45% recall, and 96.45% F1-score on held- out validation split, which shows even-handed performance across classes. It is a depth wise separable architecture resulting in low-latency inference with an average mean performance of about 17.95 MS per image on mid-range mobile platforms, which makes it appropriate in resource-constrained deployments. All animals in the categories can have a digital identity based on QR, which holds breed and history information, making it a tool to track them over time. The proposed system will allow decreasing the number of errors in manual entries and enhance the quality of information systems on livestock because it is implemented using high-precision visual recognition with persistent per-animal profiles.**

***Index Terms*—Recognition in cattle breeding, lightweight CNN, MooNet architecture, livestock identification on mobile phones, traceability via QR-codes, field-level image-based cattle identification.**

I. INTRODUCTION

Cattle and buffalo are still an important part of world food systems that play a role in dairy production, meat production, rural living, and sustainable agriculture. With the digital livestock management systems becoming more and more widespread, it is necessary to have proper and up-to-date records of every animal in order to trace the productivity and breeding programs, disease trends, and even evidence-based policy- making. Of these records, breed information is the most influential since it is used to determine the potential of genetic potential, growth patterns, resistance to diseases and adaptation to a particular environment.

In spite of its significance, in most areas breed identification remains a manual process and this is normally done by field surveyors, veterinary personnel, or extension workers. Most of these staff are not specifically trained in breed recognition and manual identification is likely to be inaccurate due to visual similarities between indigenous and crossbreed cows. The task is complicated further by real-world conditions, such as variable lighting, motion blur, partial oculation and background clutter, which result in inconsistent or inaccurate entries into livestock databases.

The errors are not only on a personal level but they are slowly compromising the dependability of huge livestock information systems. The wrongful classification of breeds distorts statistics on population, diminishes the efficiency of breeding programs, disrupts traceability processes and constrains the validity of research results. These discrepancies over time prevent the capability of the stakeholders, such as farmers, policymakers, and researchers, to make sound decisions. This leads to an obvious necessity of devices facilitating the process of consistent and objective identification of breed in real fieldwork.

New fields of computer vision and deep learning provide prospects of tackling these challenges. Convolutional neural networks (CNNs) have demonstrated an unprecedented performance in classification tasks associated with images, even in cases where the difference between classes is not very clear. Mobile Net and CNN derivatives The existence of lightweight CNN architectures (Zhang et al. 2018), like MobileNet (Howard et al. 2017), indicates that high-accuracy models can be efficiently run on mobile and edge devices. Such a feature is essential to the field setting, where connection can be weak and real-time predictions require processing on the device.

In response to these needs, we present the MooNet which is a lightweight CNN that is formatted to be used in mobile cattle breed recognition across varying field conditions. MooNet takes field-captured images and gives ranked breed predictions, which is a decision-support tool that can be deployed in a low-resource environment. In order to provide continuity on identity management, each animal is assigned a digital profile with QR linkage that it can be retrieved and the system could record the breed, health and ownership information of the animal on multiple visits. The offered solution improves the reliability, scalability, and the quality of livestock at a because of its ability to combine effective visual classification and an effective digital traceability mechanism.

RELATED WORK

1.1. CLASSICAL COMPUTER VISION METHODS

Initial studies on cattle breed identification were based mainly on the classical computer vision techniques, which were contour extraction, shape descriptors, color histograms and texture analysis. These were custom hand-built feature methods, which were computationally inexpensive but very sensitive to variations in the image. The shifts in light, pose, or background, which would seem minor, could lead to dramatic performance degradation and to a slower application of this method in the field where the quality of an image could not be regulated.

1.2. DEEP LEARNING FOR LIVESTOCK RECOGNITION

Deep learning application provided significant advancements (Haq et al. 2021) to the classification of livestock images. The CNN based models, such as VGG (Simonyan and Zisserman 2014), ResNet (He et al. 2016), Efficient Net (Tan and Le 2019), and Mobile Net, have been used to perform tasks of identifying breeds and other types of livestock identification. Although these studies are highly accurate on curated data, the majority of them are based on controlled image sets with clean backgrounds and optimal lighting. Consequently, models tend to fail when used on field images with noise, shadows, occlusion, uneven compositions to name but a few.

1.3. DIGITAL IDENTITY AND TRACEABILITY SYSTEMS

Similar studies in livestock informatics have discussed the digital tagging methods that have been used, including RFID chips, electronic ear tags, QR codes (Dwivedi and Sahu 2019), and mobile-based identity tracking. These solutions enhance trace ability, where each animal is connected to a unique digital data that holds demographic or health related data. Nevertheless, the majority of the current models consider QR codes or tags as fixed identifiers and lack the automated breed recognition, which restricts their practical use in the situation when identity verification and breed classification need to be two aspects cooperating with each other.

1.4. RESEARCH GAPS

Despite the promising results obtained by CNN-based models in choosing livestock, and digital identities to increase traceability, these two elements are not often combined in the same workflow. The current strategies typically ignore the complexity of noisy field images and the necessity of making inferences within the device in low-resource settings. In addition, not many systems integrate real time classification and long-term consistency of digital profile. MooNet seeks to fill these gaps by combining lightweight mobile-based recognition of livestock with identity management based on QR codes and creating a viable and scalable real-world livestock data system solution.

II. METHODOLOGY

2.1 SYSTEM OVERVIEW

The suggested system combines an application of a mobile-friendly deep learning model with a QR-based digital identity mechanism to achieve effective cattle breed recognition in field real-world application. As shown in Fig. 1 illustrate how a user takes a photo of the animal using a mobile phone. The image is sent to the backend, and the lightweight MooNet CNN is used to process the image and generate a ranked list of breed predictions. The prediction and metadata are then saved in a digital profile to which a unique QR code of the animal is attached once verified. The scan of the QR code will be used to retrieve the same profile during succeeding visits to maximize consistency over long-term and prevent repetitions.

2.2 DATASET DESCRIPTION

The data set comprises of about 12,000 annotated cattle pictures (Community 2025) taken under diverse field conditions such as variations in lighting, backgrounds clutter, and occlusions, and camera angles (Huang et al. 2022). The dataset is a mix of indigenous and crossbred cattle as illustrated in the Fig. 2 realistic as far as diversity is concerned. It was divided into 50:50, and 6,000 images of training and 6,000 images of validation were obtained. This is a balanced setup that would guarantee a strong evaluation without further biasing the dataset.

2.3 PREPROCESSING PIPELINE

Each input image was down sampled to 384x384 to have a compromise between computation time and the capacity to resolve finer breed-specific details (e.g., horn curvature, facial patterns). The mean and the values of variance, which are often used with ImageNet-pretrained models, were used to normalize standard RGB. To induce the fluctuations experienced in field images, a number of data augmentation methods were used in training, such as random rotations (+-15deg), horizontal flips, color jitter, and a small zoom. These augmentations enhance the model to be robust to noise, motion blur and non- inform imaging in the real world.

2.4 MOONET ARCHITECTURE

The MooNet is a light CNN architecture that has MobileNetV4 as its inspirer, but it is optimized to be implemented on mobile devices with depth wise separable convolutions and inverted residual blocks. As shown in Fig. 3 architecture, the model has an initial convolution block, then a sequence of inverted residual layers (Sandler et al. 2018) that gradually acquire spatial and structural information that can be used to identify breeds. The compact feature representation is a global average pooling layer,

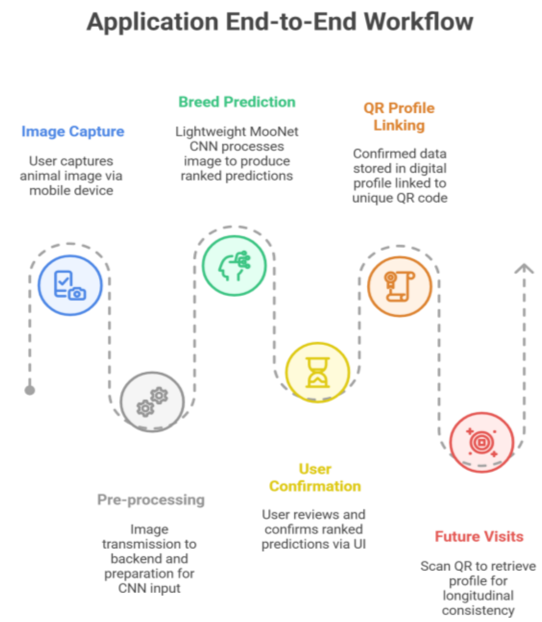

FIG. 1 OVERALL WORKFLOW OF THE PROPOSED MOONET SYSTEM

and it is sent to the classification head that consists of a fully connected layer followed by SoftMax output across all breeds of cattle. The design is very precise with a low computational cost, hence MooNet can be applied in devices of low processing capability.

2.5 TRAINING STRATEGY

The PyTorch implementation of the model was started with pretrained weights to increase the speed of convergence. The decay schedule of learning-

rate was staged, which was inspired by the setting presented in the original training notebook:
Stage 1: 8 epochs @ (2 ×10−3)
Stage 2: 33 epochs @ (3 ×10−4)
Stage 3: 10 epochs @ (3 ×10−5)
Stage 4: 5 epochs @ (3 ×10−6)

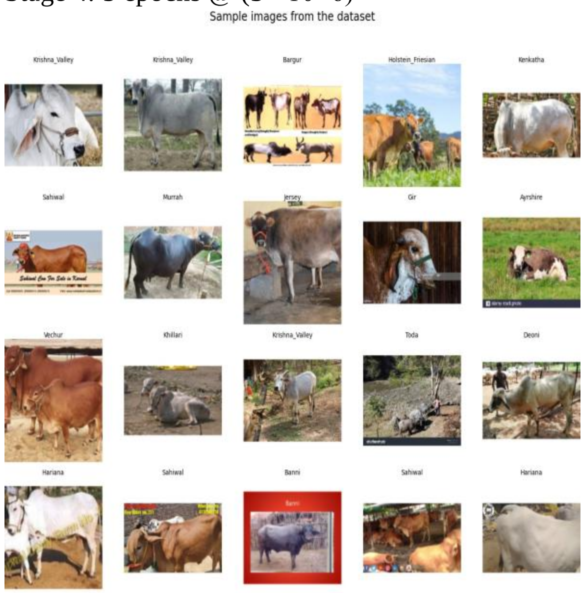

FIG. 2 SAMPLE IMAGES FROM THE DATASET ILLUSTRATING REAL-WORLD VARIATIONS IN LIGHTING, ANGLE, OCCLUSION, AND BACKGROUND

They were cross-entropy loss and Adam optimizer. A batch size of 64 was chosen to fit into the memory of the GPUs. This progressive refinement plan permitted MooNet to eliminate general ImageNet characteristics on to cattle-specific ones with consistent convergence.

2.6 QR-BASED DIGITAL IDENTITY SYSTEM

Once the animals have been predicted, the QR codes of animals are created. This QR code will connect to the permanent database with the information about the breed, medical history, age, and data about its owners, and the information about its previous visits. Scanning the QR code gets the same digital profile, which removes the occurrence of manual entries as shown in Fig. 4 Longitudinal analysis and auditability are also feasible with the QR-based system, which is why the framework can be applied to regions that have varying digital infrastructures.

2.7 MOBILE DEPLOYMENT WORKFLOW

The system was implemented based on a modular architecture, which is a mobile Progressive Web App (PWA) written in React and Next.js, Fast API backend, and a Torch Script-optimized inference engine. Computations of the predictions can be done on the server or on-device by ONNX Runtime based on device capability and network accessibility. This architecture allows low-latency inference and operates in both online and intermittent-connectivity settings, which makes MooNet appropriate to be deployed worldwide to rural or remote areas.

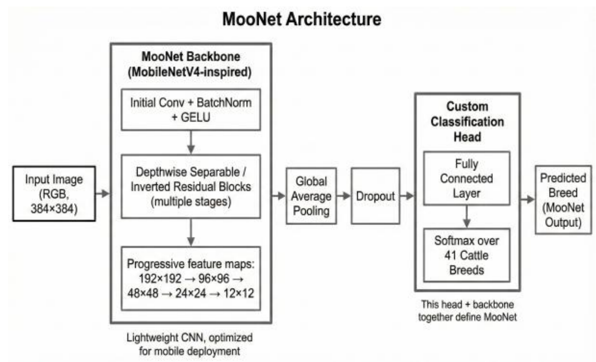

FIG. 3 LAYER-WISE ARCHITECTURE OF THE PROPOSED LIGHTWEIGHT CNN MODEL MOONET

FIG. 4 QR-BASED DIGITAL TRACEABILITY FRAMEWORK USED FOR PERSISTENT IDENTITY LINKING

2.8 EXPLAINABILITY USING GRAD-CAM

In order to enhance transparency and user confidence, Grad-Cam visualizations were produced (Selvaraju et al. 2017) in order to enforce discriminative areas that affected the predictions of MooNet. These heatmaps, as illustrated in Fig. 5 will assist users to know why a certain breed was proposed particularly in case of an ambiguous case which looks like a closely related breed.

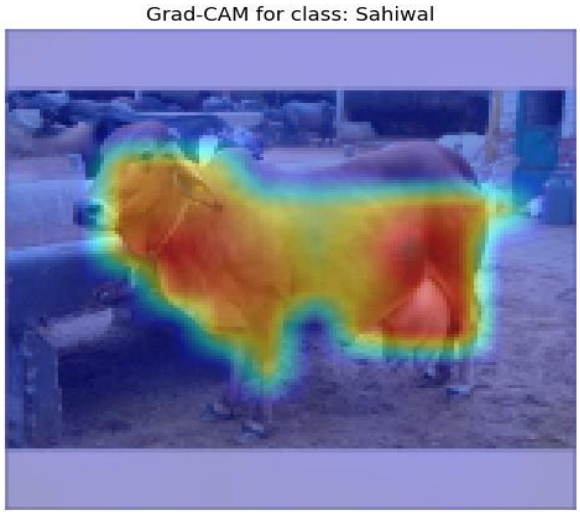

FIG. 5 GRAD-CAM VISUALIZATION HIGHLIGHTING REGIONS DRIVING MOONET'S PREDICTION

2.9 OVERALL VALIDATION PERFORMANCE

The performance of the entire validation process is presented in Fig. 6. MooNet was tested on a validation set of about 6,000 images of field-condition cows. The model achieved:

2.9.1 Accuracy: 96.45%
2.9.2 Precision: 96.47%
2.9.3 Recall: 96.45%
2.9.4 F1-score: 96.45%

The high agreement between accuracy, precision, recall, and F1-score mean that MooNet achieves a balanced trade-off between false negatives and false positives on all breeds.

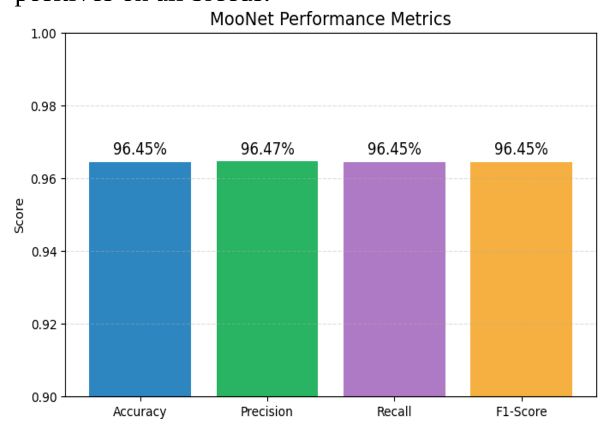

FIG. 6 SUMMARY OF EVALUATION METRICS FOR MOONET ON THE VALIDATION DATASET

2.10 CLASS-WISE PREDICTION BEHAVIOUR

Fig. 7 illustrates the split of the images in training and validation set of all breeds. Although the classes were not balanced, with some having over 400 images and others with less than 100, MooNet maintained a good accuracy to all classes.

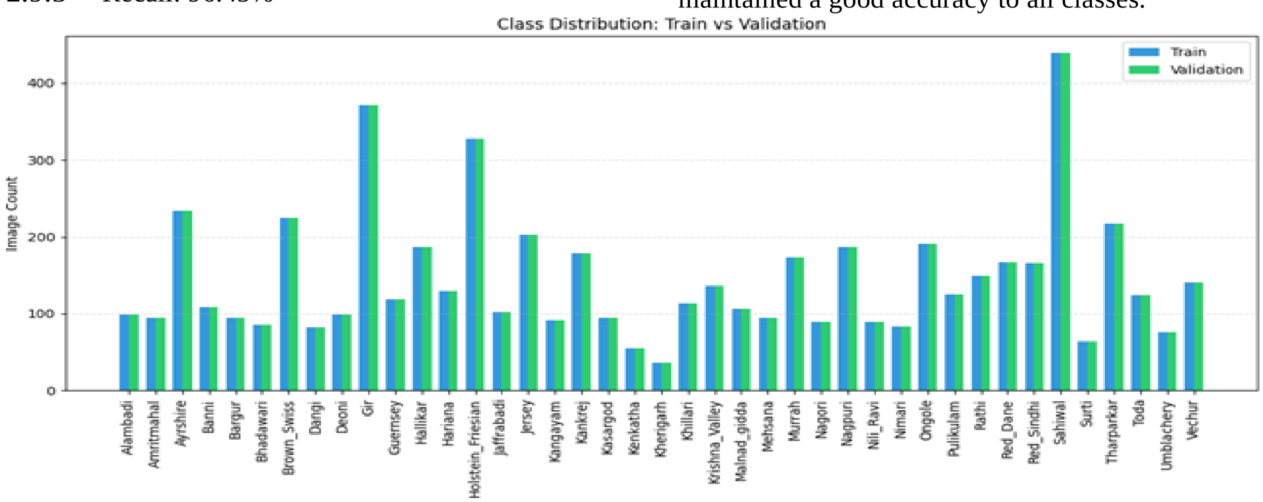

FIG. 7 DISTRIBUTION OF CATTLE IMAGES PER BREED IN THE DATASET

The entire confusion matrix of all the breeds is shown in Fig. 8. The large diagonal shows that MooNet has successful accuracy in the breed. Misclassifications are mostly common among closely related breeds whose physical characteristics are similar (Ramirez et al. 2020).

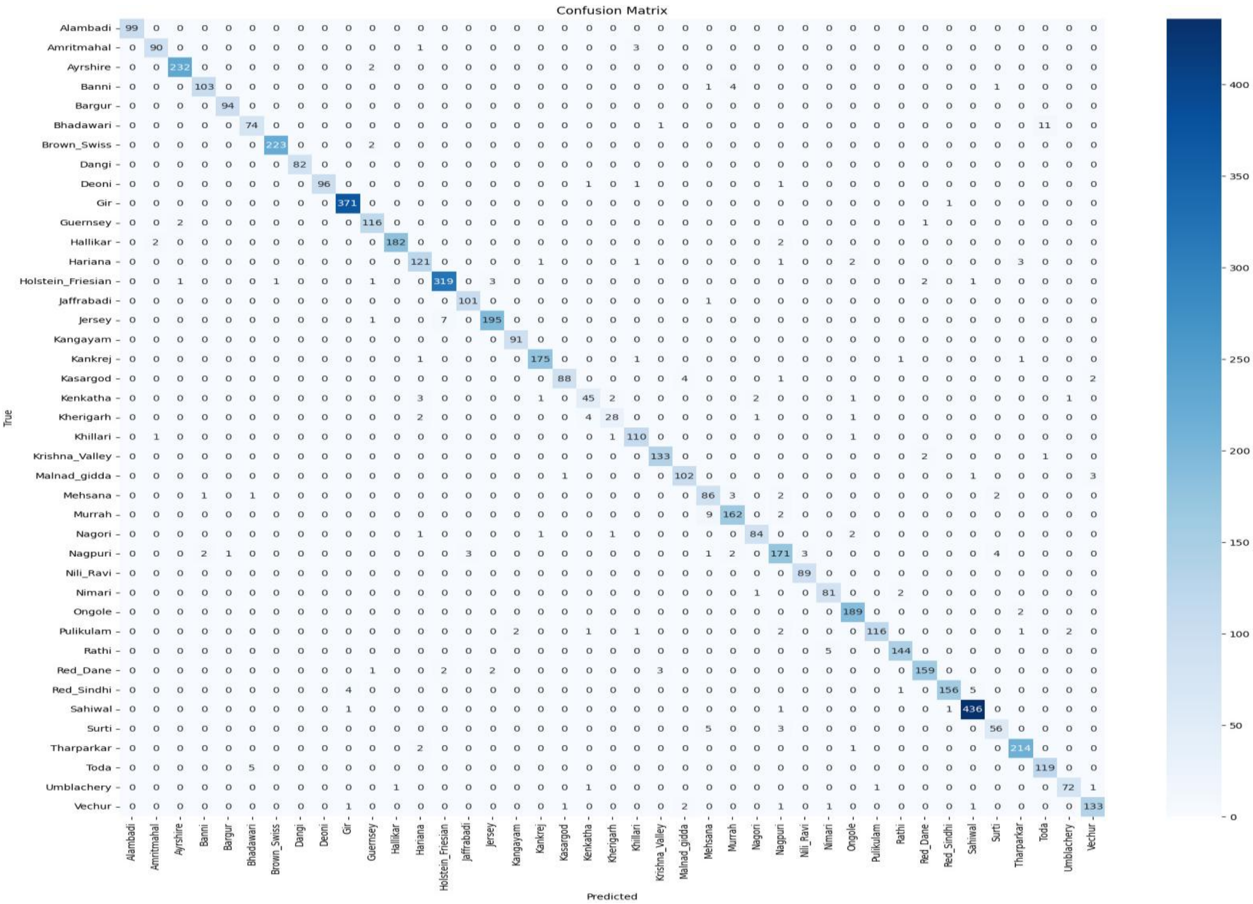

FIG. 8 CONFUSION MATRIX SHOWING CLASS-WISE PREDICTION BEHAVIOUR ACROSS ALL EVALUATED BREEDS

2.11 PERFORMANCE OF MODEL COMPLEXITY AND INFERENCE

As indicated in the summary of the architecture, MooNet has:

2.11.1 Trainable parameters: 36.4 million

2.11.2 Total parameters: 39.4 million

2.11.3 Model size: ~140 MB

2.11.4 Compute: 7.37 GMACs

The performance of inference was tested on 100 runs on mid-range hardware as shown in Fig. 9 and Fig. 10. The results of the latency recorded were:

2.11.5 Minimum: 16.72 MS

2.11.6 Maximum: 28.41 MS

2.11.7 Mean: 17.95 MS

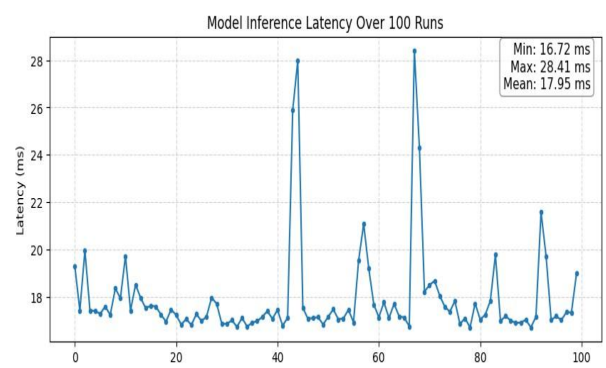

FIG. 9 MODEL INFERENCE LATENCY OVER 100 RUNS

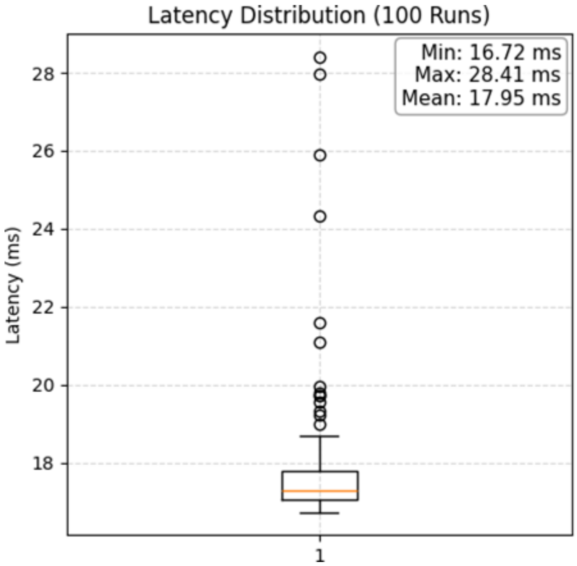

FIG. 10 LATENCY DISTRIBUTION SHOWING MINIMUM, MAXIMUM AND MEAN INFERENCE TIME

2.12 STRENGTH OF PERFORMANCE IN REAL FIELD LABORATORY CONDITIONS

The validation dataset had samples with:

2.12.1 non-uniform and exterior lighting.
2.12.2 frontal, side and diagonal poses.
2.12.3 partial occlusion (handlers, cattle overlap)
2.12.4 motion blur
2.12.5 cluttered backgrounds
2.12.6 multiple animals in frame

In spite of these difficulties, MooNet continued to achieve more than 96% accuracy, which validated that it generalizes well even when it is not in clean laboratory-like scenarios.

This strength is attributed to:

2.12.7 384x384 high-resolution inputs
2.12.8 potent augmentation pipeline.
2.12.9 Receptive field enhancements of MobileNetV4.
2.12.10 optimal residual depth on fine-grained texture recognition.

2.13 ERROR ANALYSIS

Misclassifications were mostly in cases where:

2.13.1 colors between breeds were almost identical.
2.13.2 analysis of horn curvature was not noticeable.
2.13.3 faces or humps were in part covered.
2.13.4 lighting had a serious effect of diminishing visible texture.

Grad-CAM visualizations (as presented above in Methodology) revealed that the correct predictions would be associated with attention to:

2.13.5 hump curvature
2.13.6 facial markings
2.13.7 horn structure
2.13.8 dorsal silhouette

The error prediction was frequent whenever MooNet focused on irrelevant areas like:

2.13.9 background clutter
2.13.10 bright reflections
2.13.11 nearby overlapping animals

These results are in conformity with past research studies in fine-grained livestock classification.

III. DISCUSSION

These findings of MooNet indicate that it is possible to obtain high accuracy in fine- grained classification of cattle breeds with lightweight convolutional design, despite the presence of realistic fields. The overall accuracy of the model is 96.45 and it is consistent even when the pose, the lighting, and the background complexity change. It means that the applied optimization approaches, including depthwise separable convolutions, high-resolution input, and a large augmentation pipeline, contribute to the increased robustness of the model to a great extent.

The fact that there is a slight difference between the accuracy, precision, recall and F1-score is another significant observation. This homogeneity implies that MooNet is not skewed in favor of dominant or majority classes, which is frequent in livestock data where some breeds are represented by a much larger cohort of samples. The confusion matrix validates this hypothesis that the majority of the misclassifications are with breeds whose visual appearances overlap with each other, as noted in previous literature of livestock-recognition.

The performance inference reveals the appropriateness of MooNet to execute in low-resource settings (Alam et al. 2023). The model, with a mean latency of 17.95 ms with repeated mobile grade tests, can be used to support real time classification in rural or remote areas where there is limited computational resources. The feature is essential to User who often use portable gadgets that have limited computing capability.

Moreover, the digital traceability based on QR and the classification pipeline would be a crucial benefit, which is not generally considered in previous studies. Constant digital identity will enable constant record management across visits and the minimization of human error as well as a reliable longitudinal monitoring of every animal. Such a visual AI analysis and digital tagging combination constitute a viable, scalable workflow that can be used in various geographic areas.

Generally, the results show that MooNet is optimal in accuracy, efficiency and practicality in deployment. Although the model is effective, future enhancements can be aimed at dealing with visually ambiguous breeds, increasing the performance in low-light conditions, and multi-view or video-based recognition to eliminate the need to rely on one picture.

IV. CONCLUSION AND FUTURE WORK

This paper introduced MooNet, a small convolutional neural network, which is capable of predicting the breed of cows in the actual field scenario with high confidence. The proposed framework addresses two key issues in livestock data collection, namely the challenge of identifying similar-looking breeds by hand and the lack of uniformity in the long-term record of animals, by enhancing the design of the mobile-first model with a QR-based digital identity system. The data presented in the experiment shows that MooNet is characterized by high and balanced performance on all metrics of evaluation, in even the situation of testing on noisy, unstructured images that are characteristic of a real-world field. This validates the fact that the model can be used to generalize successfully on clean laboratory data.

Breed recognition combined with continuous QR-linked profiles also enhances the utility of the system as the system ensures a constant access to the information about an animal and guarantees its accuracy in several visits and devices. By doing so, a more reliable livestock dataset can be created, and they can be used in a vast variety of applications such as health monitoring, breeding programs, and digital livestock management platforms.

The model has good performance in most aspects but a small number of cases are misclassified, particularly when it comes to similar indigenous and crossbred animals, and this is an area where improvements can be made. The future directions could involve cross-regional datasets, multi-view image inputs, automatic quality checks of image capture, and light model versions optimized to work with ultra-low-power devices. The use of time, video-based recognition or multimodal cues (gait or voice patterns) can also be used to increase strength.

On the whole, MooNet is a feasible and scalable solution to globally deployable livestock recognition systems, which has a high accuracy, portability, and integration ease in a real-world agricultural environment.

V. ACKNOWLEDGMENT

The authors thank the open-source research community with their whole heart because they have provided high-quality tools and datasets that can be used to conduct aca- demic research. The image of a cow that was used in this study was given by Kaggle, which was essential in allowing training and evaluation of the proposed model at a very large scale. Another aspect that is highlighted by the authors is the assistance that the contributors of the PyTorch and TensorFlow ecosystems gave their publicly available deep-learning libraries to aid their MooNet implementation and optimization efforts.

VI. COMPLIANCE AND ETHICAL CONCERNS

The current research was carried out on publicly available, open-access data, so no personal, confidential or any other personal information was utilized at any point. All the images of cattle used in the training and validation were obtained only in the Kaggle public repository that allows research and non-commercial use of its datasets under the dataset license. There were no images of farms, individuals, and organizations, no field surveys of live animals were conducted to develop the MooNet.

The suggested model will not store or process sensitive information regarding the owners of animals, geolocation, or commercial farm activities. QR-based identity pro- files as outlined in this paper are in theory and are not supposed to have personal information in the present implementation; this is subject to large-scale implementations. In this sense, the research adheres to the general guidelines of using data, privacy, and responsible AI development.

There were no experiments involving live animals, and the work is not conducted on invasive and harmful procedures. Computational experiments were all executed on offline machine learning pipelines with the help of open data, which was in line with international standards of conducting research with non-human participants. The authors confirm that the study complies with the ethical requirements of Springer and other communities of research.

DECLARATIONS

FUNDING

No particular grant was given to this research by either government, business or non- government granting agencies.

DATA AVAILABILITY

The datasets that have been used in the ongoing research are openly accessible in the Kaggle repository, as presented in (Community 2025). There was no other proprietary data created or utilized by this work.

COMPETING INTERESTS

None of the authors state that they have competing interests to this manuscript.

AUTHOR CONTRIBUTIONS

Conceptualization, model design and implementation of MooNet were headed by U. Tiwari. Curating data, evaluating experimentally, and analyzing it were done by N. Bisht and N. Kumari. Every author worked on the writing, revision and approval of the final manuscript.

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