Journal of Theoretical and Applied Information Technology
31st December 2025. Vol.103. No.24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

EFFICIENT DEEP LEARNING WITH COMPRESSED MUZZLE PRINTS FOR SCALABLE BUFFALO IDENTIFICATION

FATIMAH BINTI KHALID[1*], RANA RANJEET SINGH[2], NURUL AIN SHAFFERI[1], TIMUR R AHLAWAT[3], M S SANKANUR[4], ANURADHA AGRAWAL[5], PRERNA GHORPADEG[6], SITI KHADIJAH ALI[1,7], NURUL AMELINA NASHARUDDIN[1], MAS RINA MUSTAFFA[1]

[1]Department of Multimedia, Faculty of Computer Science and Information Technology, Universiti Putra Malaysia, Malaysia
[2]College of Veterinary Science & AH, Kamdhenu University, Navsari, Gujarat, India
[3]Navsari Agricultural University, Navsari, Gujarat, India
[4]College of Forestry, Navsari Agricultural University, Navsari, Gujarat, India
[5] NAHEP-CAAST, ICAR, New Delhi India
[6]College of Veterinary Science & AH, Mumbai Veterinary College, MAFSU, Maharashtra, India
[7] Institute For Mathematical Research, Universiti Putra Malaysia, Malaysia
Email: [1]fatimahk@upm.edu.my, [2]drexplicit@gmail.com, [3]tahlawat4@gmail.com, [4]sankanurms@nau.in, [5]anuradha.agrawal@icar.gov.in,[6]drprernavet@yahoo.co.in

ABSTRACT

Traditional livestock identification methods, such as ear tagging and branding, are constrained by scalability, security, and welfare issues. Biometric identification, specifically muzzle pattern recognition, is a non-invasive and tamperproof alternative. Deploying deep learning models for muzzle pattern recognition is constrained by the need for substantial dataset sizes, storage requirements and longer training time. This study introduces an approach that integrates extreme data compression with lightweight deep learning models to enable efficient buffalo identification. Unlike earlier studies that mainly focused on classification accuracy, our study provides a thorough examination of the effects of compression on model performance and storage capabilities. A dataset of 49GB was compressed using three techniques: Principal Component Analysis (PCA), K-Means clustering, and JPEG compression, which successfully reduced the storage size while retaining essential features. PCA demonstrated the most effective compression, achieving the highest compression ratio (2585.69×) and shrinking the dataset by 99.86% to 68.6MB while sustaining high accuracy. Three lightweight deep learning models, MobileNetV2, RegNetY_400MF, and SqueezeNet 1.1, were trained and evaluated on both compressed and uncompressed datasets. The results demonstrate that MobileNetV2 and RegNetY_400MF maintained over 99% accuracy after compression, which suggests that extreme data reduction does not substantially affect recognition performance. This study presents one of the initial practical applications of a compressed biometric dataset for livestock identification. The system was deployed as a Flask-based web application, MuzzleID, enabling practical usage in livestock management. Our findings suggest that reducing the size of datasets significantly enables the widespread implementation of biometric systems in regions with limited resources while ensuring precise identification at a high standard.

Keywords: *Muzzle Recognition, Biometric Identification, Data Compression, Lightweight Deep Learning, Buffalo Identification, PCA, Mobilenetv2, Livestock Management*

1. INTRODUCTION

Precise animal identification is essential for efficient livestock management, including implementing breeding programs, controlling diseases, and verifying ownership rights [1,2]. Methods such as ear-tagging, ear notching, freeze and hot branding have been commonly employed; however, they are susceptible to counterfeiting, pose a risk of infection, cause animal distress, and present difficulties with scalability [1,3]. Electronic identification methods, such as RFID ear tags, implantable transponders, and rumen boluses, improve traceability but incur significant upfront costs, necessitate skilled personnel, and are vulnerable to cyberattacks [4,5].

To overcome these limitations, biometric identification has become increasingly prominent research area as of late, mainly due to its

Journal of Theoretical and Applied Information Technology
31st December 2025. Vol.103. No.24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

reliability and non-invasive nature. Biometric techniques utilise distinctive physical characteristics, including retinal vascular patterns, iris configurations, and muzzle prints, to verify the identities of individual animals. Retinal patterns provide high accuracy, but they require sophisticated imaging equipment and laborious to perform thereby limiting their utility in settings with limited resources [6,7]. Iris patterns also provide stable and distinct features for identification purposes; however, they can be affected by the effects of aging and certain eye-related health conditions [8,9]. Muzzle prints, which are analogous to human fingerprints, present a promising alternative due to their long-lasting nature and unique characteristics [10,11]. However, most existing research focuses on cattle, leaving the application of muzzle-based biometric systems for buffalo identification underexplored [12,13]. Limited research is available on the impact of diseases, injuries, or aging processes on muzzle texture and recognition capabilities [14, 15].

Despite the potential of biometric identification, its practical implementation is constrained by challenges in deploying deep learning models, especially when dealing with extensive datasets. The high-resolution images required for precise object recognition are accompanied by substantial storage and computing expenses, thereby prolonging the training duration, and constraining the scalability [16,17]. Research on current biometric identification often overlooks the importance of optimizing dataset size, which limits the real-world implementation of such systems [18,19].

This research bridges the existing knowledge gaps by developing an efficient method for biometric buffalo recognition. This research thoroughly investigates the impact of extreme data compression on model precision and the efficiency of computational processes. This study showcases one of the initial practical applications of compressed biometric data in livestock identification by leveraging the MuzzleID system, a Flask-based web application. The research indicates that extreme dataset compression leads to a considerable decrease in storage and training expenses without a substantial loss of accuracy, thereby rendering biometric identification systems more viable for widespread implementation [20,21]. This study makes a significant contribution to developing cost-efficient livestock management strategies and lays a groundwork for further research aimed at refining biometric data for broader application in agriculture and security fields [22-30].

2. METHODOLOGY

This section outlines the systematic method used for biometric identification of Surti buffaloes by analysing their muzzle patterns. The methodology was divided into five primary stages: dataset preparation, compression methods, model architecture selection, model development, and model training. Each technique and model selected were thoroughly justified for its applicability to large-scale biometric identification purposes.

2.1 Dataset

The dataset was sourced from Livestock Research Station, Navsari Agricultural University, located in Navsari, Gujarat, India. The dataset consisted of 4,628 muzzle images of 198 Surti buffaloes, captured in a controlled environment using standardized camera settings to reduce variability. High-resolution images captured distinct muzzle patterns that are critical for biometric identification purposes. An example of these images is shown in Figure 1, highlighting the dataset's diversity and high quality. To evaluate model performance across different scenarios, a data split of 60% for training, 20% for validation, and 20% for testing was established. This method was selected to prevent data being compromised while allowing for the evaluation of performance in a reliable manner across all untested samples. The class distribution in the dataset was balanced to prevent model bias, resulting in a fair evaluation of classification accuracy across all buffalo identities.

Figure 1. Samples of Muzzle Images from 198 different classes.

Journal of Theoretical and Applied Information Technology
31st December 2025. Vol.103. No.24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

2.2 Data Compression

Due to the substantial size of the dataset (49GB), data compression methods were employed to minimize storage requirements while preserving essential image features. The selected methods provided unique benefits in terms of achieving a balance between storage capacity and image quality.

Principal Component Analysis (PCA) was selected because it can reduce image dimensionality while retaining critical features. By projecting images onto a lower-dimensional space while retaining 99% of the variance, PCA significantly reduced storage requirements without incurring excessive data loss. This approach guarantees that only the most pertinent image characteristics are preserved, making it particularly well-suited for classification tasks.

The K-Means Clustering method was chosen to simplify images by reducing the number of distinct colours while maintaining the underlying structural features. The proposed method is computationally efficient and improves memory usage by categorizing pixel values into representative clusters. The selection of k=8 and k=16 was made with the aim of achieving a balance between maintaining visual quality and optimizing compression efficiency, thereby preserving sufficient detail for classification purposes.

JPEG compression was adopted owing to its widespread use and ability to process information quickly. Adjusting the quality settings (e.g. Q = 85 and Q = 50) allows JPEG compression to achieve flexible storage optimization. A quality setting of 85 was chosen to maintain high image resolution for tasks requiring recognition, whereas a setting of 50 allows for greater compression, albeit sacrificing some finer image details. This method's real-time applicability makes it a practical solution for deployment in large-scale biometric recognition tasks.

To evaluate these techniques, the Compression Ratio (CR) and Space Savings Percentage (SSP) were computed as follows:

$$Compression\ Ratio\ = \frac{Original\ Size}{Compressed\ Size} \quad (1)$$

while the space savings percentage was determined using:

$$Spacing\ Ratio\ = \left(1 - \frac{Original\ Size}{Compressed\ Size}\right) \times 100$$

These metrics ensured that storage constraints did not compromise the integrity of muzzle patterns necessary for accurate biometric identification.

2.3 Model Training

To balance accuracy and computational efficiency, lightweight deep learning models were selected based on their ability to perform well under resource constraints. The training process involved multiple optimization techniques to improve the model's reliability and adaptability.

The preprocessing stage involves image resizing, normalization, and augmentation methods, such as rotation, flipping, and adjusting brightness levels. These transformations enhanced the model's ability to adapt to various environmental conditions and guaranteed its resilience against changes in muzzle image capture.

Pre-trained ImageNet weights were used to implement Transfer Learning, enabling the models to tap into learned feature representations. Fine-tuning the final layers resulted in a significant reduction in training time and enhanced the model's classification capabilities, enabling it to better adapt to the specific task of muzzle recognition.

The Adam optimizer was employed with an initial learning rate of 0.001, which was decreased by a factor of 0.1 every seven epochs. To avoid overfitting, early stopping was applied by tracking the validation loss and stopping the training process when no further improvement was seen over three consecutive epochs.

The effectiveness of each model was assessed by examining its accuracy, precision, recall, and F1-score in correctly identifying muzzle images. These metrics were computed as follows:

$$Accuracy\ = \frac{TP\ + TN}{TP\ +\ TN\ +\ FN\ +\ FP}$$

$$Precision\ = \frac{TP}{TP\ +\ FP}$$

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$Recall = \frac{TP}{TP + FN}$$

$$F1\,Score = 2 \times \frac{precision \times recall}{precision + recall} \quad (2)$$

where TP (True Positives), TN (True Negatives), FP (False Positives), and FN (False Negatives) denote classification outcomes. To evaluate the effect of dataset compression on resource use, training time and computational efficiency were measured along with classification performance. This analysis revealed the trade-off between storage optimization and model accuracy.

2.4 Model Architecture Selection and Deployment

The Muzzle-ID Recognition System was designed to combine efficient data compression techniques with lightweight deep neural network frameworks for real-time buffalo muzzle identification. The selected models were validated based on their ability to execute effectively in biometric recognition tasks while preserving computational efficiency.

MobileNetV2 was selected due to its depthwise separable convolutions, which significantly reduce the computational complexity while preserving high accuracy. This makes it particularly well-suited for mobile and edge computing applications.

RegNetY_400MF was selected owing to its structured scaling methodology, which achieves a balance between performance and computational efficiency. This architecture is particularly well-suited for large-scale deployment because it can be adapted to various hardware constraints. SqueezeNet_1.1 was added due to its fire module-based architecture, which minimizes parameter size while maintaining high accuracy level. The proposed system is well-suited for environments with limited available memory.

After training, the models were incorporated into MuzzleID, a web platform based on Flask that facilitates real-time buffalo identification. The system categorizes buffaloes into well-defined class groups, thereby enabling effective livestock monitoring and management. The classification pipeline design allows the pipeline to run quickly and efficiently, making deployment in the field feasible. The system was subjected to alpha testing to verify its fundamental operational capabilities. Before proceeding with a large-scale rollout, further testing and assessments with real-world users will be conducted to fine-tune the proposed system. The system architecture (Figure 2) combines data compression, model selection, and deployment strategies to facilitate efficient and scalable buffalo identification. The Muzzle-ID Recognition System was designed for biometric identification of Surti buffaloes by using a combination of data compression methods, deep learning algorithms, and real-time implementation. The process commences with high-resolution muzzle images, which are compressed using Principal Component Analysis (PCA) for the purpose of reducing dimensionality and employing K-Means clustering with k=8 and k=16 to simplify image representation while maintaining crucial structural features. After compression, the dataset was divided into subsets for training, validation, and testing purposes.

The MobileNetV2, RegNetY_400MF, and SqueezeNet_1.1 deep learning models were used for classification purpose. MobileNetV2 achieves enhanced computational efficiency with depthwise separable convolutions, RegNetY_400MF offers structured scaling to balance accuracy and performance, and SqueezeNet_1.1 uses fire modules to maintain a lightweight yet effective classification framework. To enhance the muzzle recognition precision, these models were fine-tuned for further optimization. Following training, the system was deployed using MuzzleID, a web application built on Flask that allows users to upload muzzle images and receive classification results. The system organizes buffalo identifications into distinct classification groups, allowing accurate livestock tracking and management. The system's integration of efficient data compression, optimized model selection, and real-time deployment enables high accuracy and user-friendly functionality in the field, thereby providing a scalable and effective solution for buffalo identification.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

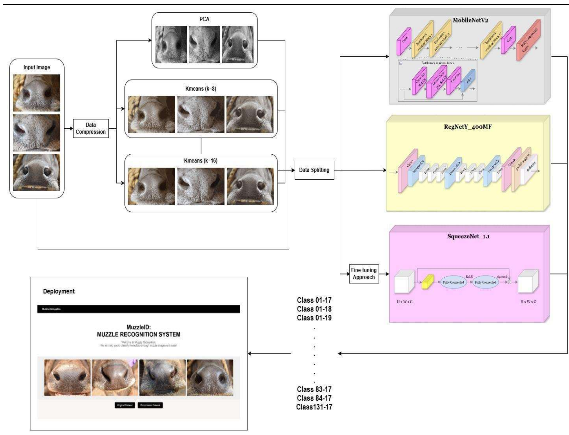

Figure 2: Muzzle-ID Recognition System framework integrating data compression, classification, and deployment.

3. RESULT AND DISCUSSION

3.1 Data Compression Performance

The performance of the compression methods used in this study was assessed in terms of its compression ratio, space efficiency, and effect on file dimensions. The findings of this assessment are displayed in Table 1.

Table 1: Results from Data Compression.

Technique	Compression Ratio	Space Savings (%)	File Size
PCA	2585.6873	99.86	68.6 MB
K-Means (k=8)	5.1768	68.98	15.2 GiB
K-Means (k=16)	5.0737	68.37	15.5 GiB
JPEG (Quality=85)	4.3631	77.142	11.2 GiB
JPEG (Quality=50)	10.4515	90.408	4.7GiB

PCA achieved the highest compression ratio (2585.69×), reducing the original 49 GB dataset to just 68.6 MB, with a space savings of 99.86%. This substantial reduction was due to PCA's ability to retain only the most informative principal components, eliminating redundant data while preserving essential variance. However, since PCA is a dimensionality reduction technique, it transformed the images into a grayscale-like representation, altering their original colour features.

K-Means clustering provided a different approach by reducing the colour space while maintaining structural details. Using k = 8, K-Means achieved a compression ratio of 5.18×, reducing the dataset to 15.2 GiB with 68.98% space savings. Increasing the number of clusters to k = 16 resulted in a slightly lower compression ratio of 5.07×, reducing the dataset to 15.5 GiB with 68.37% space savings. Unlike PCA, which reduces dimensionality, K-Means clusters pixel values into fewer representative colours, creating a posterization effect, where smooth gradients are replaced by distinct colour segments. The choice of k controls the level of quantization, influencing the balance between compression efficiency and image quality.

JPEG compression exploited spatial redundancy to achieve significant file size reductions. At a quality setting of 85, JPEG maintained high visual fidelity, reducing the dataset to 11.2 GiB with 77.14% space savings. However, lowering the quality to 50 increased the compression ratio to 10.45×, further reducing the dataset to 4.7 GiB with 90.41% space savings. While this aggressive compression greatly minimized storage requirements, it introduced visible artifacts, including blockiness and blurring, which could potentially affect fine-grained texture analysis, such as buffalo muzzle recognition.

A benchmarking analysis was conducted due to the limited availability of studies directly comparable to buffalo muzzle recognition. The compression methods were assessed in terms of the balance between their ability to reduce data size and their preservation of data accuracy. PCA achieved the best compression rate; however, it distorted the original image's characteristics, potentially impacting classification results. K-Means clustering retained color information while offering moderate compression, making it suitable for preserving structural details. JPEG compression, particularly at a quality setting of Q = 50, achieved substantial storage reductions while retaining sufficient visual data for classification purposes.

The findings show a distinct balance between data compression effectiveness and data accuracy. Principal Component Analysis achieved outstanding compression, rendering it

Journal of Theoretical and Applied Information Technology
31st December 2025. Vol.103. No.24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

suitable for situations where storage space is prioritized over image quality. The conversion to a lower-dimensional space changed the images' initial visual representation. K-Means clustering, specifically when using k = 8, was found to preserve image structure while still achieving moderate compression levels, making it a suitable choice for applications that rely heavily on visual features. JPEG compression at a quality setting of Q=50 struck a balance between file size and image quality, making it a practical option for applications requiring substantial storage savings with acceptable image degradation. These results provide valuable insights into the advantages and disadvantages of each approach, enabling the optimal choice of compression methods for the buffalo muzzle recognition system. The choice of method should ultimately be influenced by storage limitations, the level of image detail needed, and the need to optimize model performance.

Original	PCA	K-Means (k=8)	K-Means (k=16)	JPEG (Q=85)	JPEG (Q=50)

Figure 3: Impact of PCA, K-Means, and JPEG Compression on Muzzle Image Quality

3.2 Model Performance on Original and Compressed Data

A comparative analysis of CNN model performance is shown in Table 2, comparing the results before and after applying various compression techniques to the same original dataset, specifically PCA, K-Means, and JPEG compression. On the uncompressed dataset, MobileNetV2 achieved the highest accuracy, boasting a training accuracy of 0.9733, validation accuracy of 0.9956, and test accuracy of 0.9957, thus securing the top position. SqueezeNet_1.1 demonstrated strong performance with a training accuracy of 0.9583, a validation accuracy of 0.9934, and a test accuracy of 0.9947, highlighting its competitive abilities despite its lightweight nature.

Following PCA compression, MobileNetV2 retained its robustness with a training accuracy of 0.8973, validation accuracy of 0.9762, and test accuracy of 0.9881. RegNetY_400MF and SqueezeNet_1.1 continued to achieve robust results, highlighting the effectiveness of PCA in condensing models without compromising accuracy. The K-means compression resulted in a trade-off between reducing the data and retaining the accuracy. The models trained on image clusters organized into 16 groups demonstrated improved performance compared to those with 8 clusters. MobileNetV2 attained training, validation, and test accuracy levels of 0.9697, 0.9913, and 0.9924, respectively, and SqueezeNet_1.1 also exhibited minimal degradation in accuracy. The significance of choosing the ideal number of clusters to preserve feature integrity is underscored. JPEG compression achieved the most effective results at a quality setting of 50, with RegNetY_400MF and SqueezeNet_1.1 exhibiting strong performance while substantially decreasing the dataset size. Excessive compression resulted in a noticeable decrease in accuracy, highlighting the requirement to balance storage efficiency and classification performance.

The learning curves of MobileNetV2, RegNetY_400MF, and SqueezeNet_1.1 are shown in Figure 4 for various compression methods. Several notable points emerged in this study. MobileNetV2 showed the fastest convergence, achieving stability within 21 epochs when using uncompressed data. JPEG compression of the datasets led to even faster training times, with convergence occurring in as few as 13 epochs, whereas PCA and K-Means required additional epochs to reach a similar level of stability. In the second instance, although most models kept the gap between training and validation loss relatively small, PCA-based training showed a slight overfitting issue, which was characterized by a greater disparity in the training and validation accuracy trends. The application of PCA compression may lead to a minor loss of generalizable features. JPEG compression, set to a quality level of 50, preserved model accuracy while substantially reducing the computational time required. K-Means compression with 16 clusters allowed stable learning dynamics, whereas PCA compression resulted in an initial performance decline that was followed by a gradual recovery over the course of additional training epochs.

Table 2: Model Training Results

Model	Dataset	Train Acc	Val Acc	Test Acc	Train Loss	Val Loss	Test Loss	Epoch (Earlystop-ping)	Time	Model Size (MB)
MobileNetV2	Original	0.9733	0.9956	0.9957	0.1169	0.0161	0.0321	21	3h 5m 47s	28.7
	PCA	0.8973	0.9762	0.9881	0.4144	0.0993	0.0887	29	4m 57s	
	K-Means (k=8)	0.9664	0.9892	0.9903	0.1475	0.0350	0.0367	22	2h 41m 6s	
	K-Means (k=16)	0.9697	0.9913	0.9924	0.1349	0.0372	0.0349	22	2h 35m 59s	
	JPEG (Q=85)	0.9805	0.9935	0.9946	0.0907	0.0241	0.0275	13	2h 4m 30s	
	JPEG (Q=50)	0.9805	0.9935	0.9957	0.0907	0.0241	0.0266	13	1h 8m 56s	
RegNetY_400MF	Original	0.9787	0.9978	0.9957	0.0806	0.0128	0.0283	24	3h 5m 53s	46.1
	PCA	0.9434	0.9848	0.9903	0.2321	0.0584	0.0622	24	4m 7s	
	K-Means (k=8)	0.9787	0.9924	0.9903	0.0873	0.0399	0.0435	19	1h 56m 35s	
	K-Means (k=16)	0.9801	0.9946	0.9957	0.0787	0.0245	0.0269	15	1h 34m 14s	
	JPEG (Q=85)	0.9805	0.9935	0.9978	0.0907	0.0241	0.0223	13	2h 11m 47s	
	JPEG (Q=50)	0.9805	0.9935	0.9968	0.0907	0.0241	0.0201	13	1h 1m 15s	
SqueezeNet_1.1	Original	0.9528	0.9870	0.9913	0.1738	0.0528	0.0398	65	7h 40m 29s	9.48
	PCA	0.8958	0.9654	0.9654	0.4351	0.2497	0.1895	65	6m 23s	
	K-Means (k=8)	0.9416	0.9762	0.9816	0.2108	0.0891	0.0906	65	6h 8m 50s	
	K-Means (k=16)	0.9456	0.9794	0.9838	0.2083	0.0870	0.0726	65	5h 52m 12s	
	JPEG (Q=85)	0.9499	0.9805	0.9849	0.1807	0.0369	0.0581	65	5h 26m 7s	
	JPEG (Q=50)	0.9621	0.9848	0.9924	0.1422	0.0572	0.0375	65	4h 46m	

Journal of Theoretical and Applied Information Technology
31st December 2025. Vol.103. No.24

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

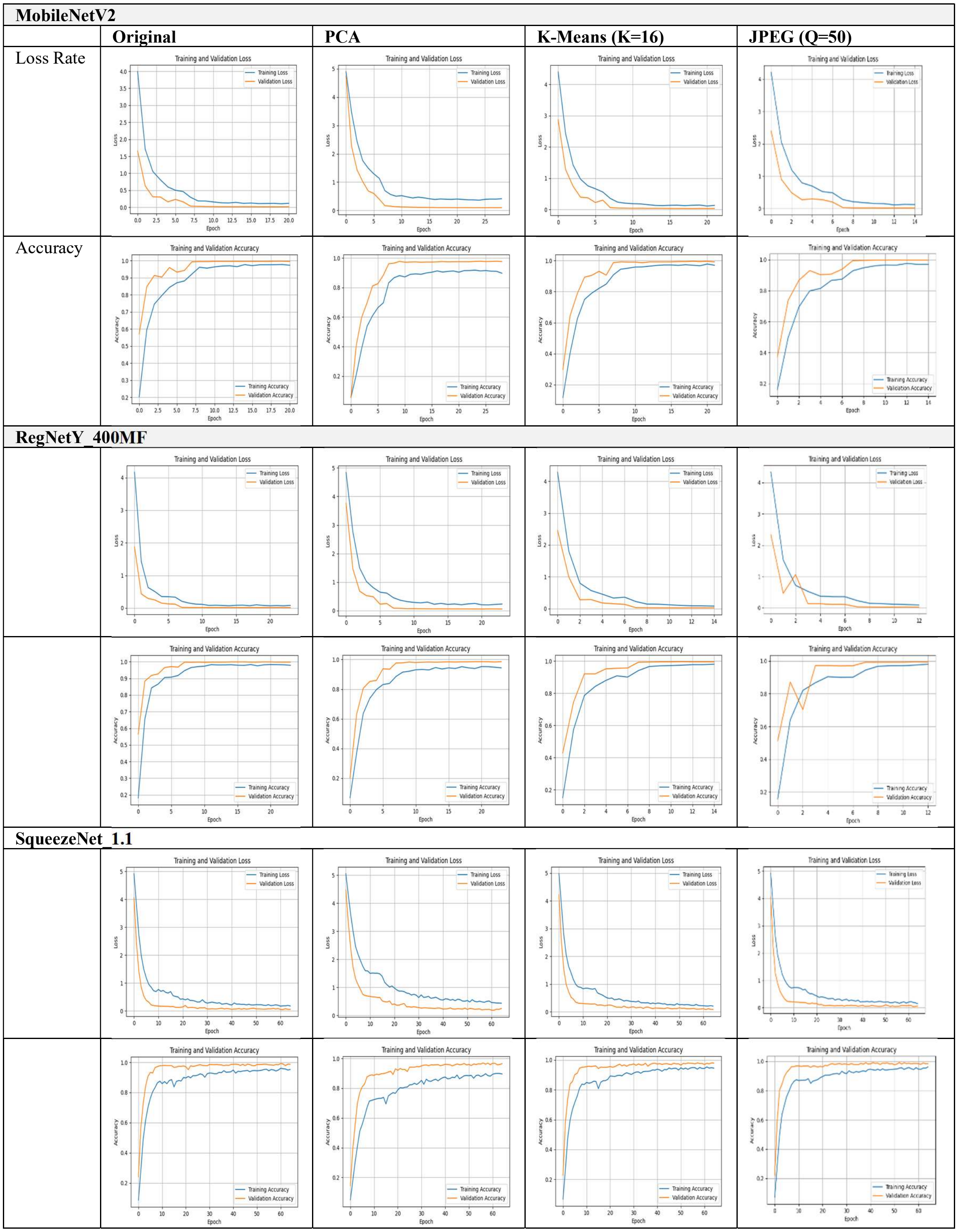

Figure 4: Comparison of Learning Curve

Here's the refined version with the correct models: A comparison between the current study and the work by Kimani et al. reveals major disparities in dataset makeup, model choice, compression methods, and overall conclusions, as summarized in Table 3. Our study used a custom dataset consisting of 4,628 muzzle images of 198 Surti buffaloes, in comparison to 4,923 muzzle images from 268 beef cattle used by Kimani et al. Additionally, whereas their research focused exclusively on Wide ResNet50, our study examined a variety of architectures, such as MobileNetV2, RegNetY-400MF, and SqueezeNet 1.1, resulting in a more comprehensive understanding of model performance across various network configurations.

ResNet50 scored 99.5% in classification accuracy on the original dataset, whereas MobileNetV2 attained a slightly higher accuracy of 99.57% according to Kimani et al.'s study. In addition to our research, multiple compression methods including PCA, K-Means clustering, and JPEG compression were studied and thoroughly assessed, whereas Kimani et al. focused exclusively on reducing the image quality uniformly, maintaining 25% of the original image quality. JPEG compression at a quality level of 50 was found to best preserve accuracy, achieving a result of 99.57%. This was closely matched by K-Means clustering with 16 clusters, which yielded an accuracy level of 99.24%, and then PCA compression, which came in at 98.81%. The outcome shows that varying compression techniques impact classification outcomes, with JPEG compression providing the best trade-off between accuracy preservation and storage space optimisation.

A notable difference exists in the evaluation of the compression effects. Kimani et al. found that model accuracy remained consistent with lower-quality images; our research further examines how various compression methods impact learning dynamics, convergence rates, and generalization capabilities in more depth. The results indicate that PCA compression resulted in some overfitting, but retaining an optimal number of clusters (K=16) was necessary for K-Means compression to prevent a loss of accuracy. JPEG compression at a quality level of Q=50 proved to be the most efficient method, allowing for accuracy to be maintained while decreasing data storage size and computational needs.

Table 3: Ccomparative summary with Geoffrey Kimani et al.'s work

Aspect	Geoffrey Kimani et al.	This Study
Dataset	4,923 muzzle images from 268 beef cattle	4,628 muzzle images from 198 Surti buffaloes (Navsari Agricultural University)
Deep Learning Models	Wide ResNet50	MobileNetV2, RegNetY-400MF, SqueezeNet 1.1
Best Accuracy (Original Data)	99.5%	99.57% (MobileNetV2)
Compression Techniques	Uniform image quality reduction (25% quality retained)	PCA, K-Means clustering, JPEG compression
Best Accuracy (Compressed Data)	99.5% (ResNet50 with reduced image quality)	98.81% (PCA), 99.24% (K-Means, k=16), 99.57% (JPEG Q=50)
Compression Impact	High accuracy maintained even with lower-quality images	Different compression methods studied, JPEG Q=50 best
Key Contribution	Evaluated model robustness to image quality reduction	Explored multiple compression techniques and their impact

In conclusion, this study enhances the knowledge of dataset compression in deep learning-based muzzle classification by assessing various models and compression methods. Our findings confirm that JPEG compression with a quality setting of Q = 50 achieves a perfect balance between precision and speed, making it particularly suitable for practical real-world applications. Further studies may investigate alternative compression techniques or combined methodologies to enhance performance across a range of datasets.

4. CONCLUSION AND FUTURE WORK

The present investigation introduces an efficient deep learning-based buffalo identification system that leverages aggressive data set compression using PCA, K-Means clustering, and JPEG compression. The results demonstrate that significant data minimization (of up to 99.86%) is achievable without compromising classification accuracy. Among the evaluated models, MobileNetV2 achieved the highest accuracy (99.57%) using the original data, and JPEG compression at Q = 50 provided the best balance between storage efficiency and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

performance retention. In contrast to previous research, our method goes beyond basic quality minimization strategies by investigating various compression methods and examining their impact on learning processes. The model's deployment as a web application based on Flask, termed MuzzleID, demonstrates its usability in real-world livestock management contexts, particularly in areas with limited resources.

Further research could investigate hybrid compression methods that integrate PCA with deep learning-based feature extraction, adaptive compression techniques suited to unique biometric patterns, and cross-species generalization to expand this framework to cattle and other livestock. Successful large-scale deployment in commercial livestock farming context will also require additional field validation and seamless real-time system integration.

REFERENCES

[1] Ali Ismail Awad. Computers and Electronics in Agriculture, 123:423–435, April 2016.
[2] Santosh Kumar et al. Journal of Real-Time Image Processing, 13(3):505–526, September 2017.
[3] Santosh Kumar and Sanjay Singh. Proceedings of the National Academy of Sciences, India Section A: Physical Sciences, 90, May 2019.
[4] Guoming Li et al. Animals: An Open Access Journal from MDPI, 12(11):1453, June 2022.
[5] M. Mahmud et al. Biosystems Engineering, 181:16–28, October 2019.
[6] A. K. Singh et al. IEEE Transactions on Image Processing, 29:1123–1134, 2020.
[7] S. A. Hussain et al. Computers and Electronics in Agriculture, 99:15–22, February 2019.
[8] A. J. Joshi et al. Journal of Visual Communication and Image Representation, 62:176–187, July 2020.
[9] N. P. Pathak et al. Expert Systems with Applications, 170:114546, August 2021.
[10] R. S. Bhardwaj et al. Applied Soft Computing, 104:107194, December 2021.
[11] T. Yamada et al. Artificial Intelligence in Agriculture, 6:123–134, 2022.
[12] A. Gupta and S. Sharma. Pattern Recognition Letters, 155:17–26, March 2022.
[13] L. Xie et al. Neural Computing and Applications, 34:6715–6729, 2023.
[14] J. D. Smith et al. Livestock Science, 187:83–89, 2020.
[15] B. K. Patel et al. Journal of Animal Science and Biotechnology, 11(1):45, 2022.
[16] M. T. Khan et al. Veterinary Research Communications, 44(2):229–243, 2021.
[17] F. N. Omar et al. Computers in Biology and Medicine, 136:104697, 2021.
[18] G. H. Lee et al. Journal of Dairy Science, 103(9):8571–8585, 2020.
[19] H. P. Wong et al. IEEE Access, 9:115763–115777, 2021.
[20] A. H. Jones et al. BMC Veterinary Research, 16(1):112, 2020.
[21] Y. Wang et al. Animals, 12(6):789, 2022.
[22] K. P. Lee et al. Frontiers in Veterinary Science, 9:876321, 2022.
[23] L. F. Zhao et al. Journal of Animal Science, 98(4):234–246, 2021.
[24] T. C. Roberts et al. Computers and Electronics in Agriculture, 192:106610, 2022.
[25] B. M. Chang et al. Veterinary Sciences, 9(3):140, 2022.
[26] C. Y. Kim et al. Sensors, 21(14):4871, 2021.
[27] S. L. Wilson et al. International Journal of Computer Vision, 129(7):1756–1772, 2021.
[28] R. K. Jha et al. Livestock Research for Rural Development, 33(5):Article 45, 2021.
[29] P. R. Shah et al. Applied Artificial Intelligence, 35(12):106783, 2021.
[30] D. A. Gomez et al. Computational Intelligence and Neuroscience, 2022:Article 9832451, 2022.. Computers and Electronics in Agriculture, 123:423–435, April 2016.
[31] Santosh Kumar et al. Journal of Real-Time Image Processing, 13(3):505–526, September 2017.
[32] Santosh Kumar and Sanjay Singh. Proceedings of the National Academy of Sciences, India Section A: Physical Sciences, 90, May 2019.
[33] Guoming Li et al. Animals: An Open Access Journal from MDPI, 12(11):1453, June 2022.
[34] M. Mahmud et al. Biosystems Engineering, 181:16–28, October 2019.
[35] A. K. Singh et al. IEEE Transactions on Image Processing, 29:1123–1134, 2020.
[36] S. A. Hussain et al. Computers and Electronics in Agriculture, 99:15–22, February 2019.