

Research Article



Automated Detection of Lumpy Skin Disease in Cattle Using Augmented Local Binary Patterns, Gabor Wavelets and Ensemble Learning

ITHAYA RANI PANNEER SELVAM^{1*}, YERRA REDDY ALEKYA RANI², RAVINDRA CHANGALA³, VANITHA SIVAGAMI⁴, DEVI MAHALAKSHMI⁴, GUL SHAIRA BANU⁵, SHALINI DIVYA PRASANNA ANBALAGAN⁶

¹Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India;

²Department of CSE (AIML), CVR College of Engineering, Hyderabad, Telangana; ³Department of CSE, Guru Nank Institutions Technical Campus, Hyderabad, Telangana; ⁴Department of CSE, Mepco Schlenk Engineering College, Sivakasi; ⁵Department of AI&DS, Er Perumal Manimekalai College of Engineering, Hosur, Tamil Nadu India; ⁶Department of CSE, PMC TECH-Hosur, India; ⁷Division of Digital Sciences, Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India.

Abstract | The increasing incidence of cattle diseases, particularly Lumpy Skin Disease (LSD), posed serious threats to animal health and livestock economies. Conventional diagnostic methods based on visual inspection and laboratory analysis were often time-consuming, costly, and subjective. To address these limitations, this study proposed an automated LSD detection framework that integrated Augmented Local Binary Pattern (ALBP) and Gabor Wavelet (GW) features with ensemble learning techniques. Initially, cattle images were divided into non-overlapping blocks, where ALBP was used to encode local texture information. Each block was further partitioned into overlapping sub-blocks, within which row-wise intensity differences were computed, followed by Local Binary Pattern (LBP) feature extraction and histogram generation. The resulting ALBP histograms from all blocks were concatenated to form a single feature vector. In parallel, the images were divided into non-overlapping patches, and GW features were extracted from each patch to capture directional, frequency-dependent, and structural characteristics, including local skin-texture variations, abnormal spots, nodules, and lesion boundaries on cattle skin. The resulting Gabor features were combined into a feature vector, and the ALBP and GW features were subsequently concatenated to form a unified representation. The combined feature vector was then provided as input to ensemble learning techniques to classify cattle images into healthy and infected categories. Experimental results demonstrated that the proposed framework achieved accuracies of 0.98, 0.97, and 0.98 on the Mendeley, Kaggle, and Veterinary Research datasets, respectively, outperforming existing approaches. Overall, the proposed framework provided a fast, scalable, and cost-effective solution for automated LSD detection, with potential to support early disease screening, timely veterinary intervention, and improved livestock management.

Keywords | Gabor wavelet, Local binary pattern, Ensemble classifier, LSD, Histogram

Received | May 05, 2026; **Accepted** | September 07, 2026; **Published** | October 13, 2026

***Correspondence** | Ithaya Rani Panneer Selvam, Department of CSE, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India; **Email:** drpithayarani@kluniversity.in

Citation | Selvam IRP, Rani YRA, Changala R, Sivagami V, Mahalakshmi D, Banu GS, Anbalagan SDP (2026). Automated detection of lumpy skin disease in cattle using augmented local binary patterns, Gabor wavelets and ensemble learning. J. Anim. Health Prod. 14(4): 1610-1622.

DOI | <https://dx.doi.org/10.17582/journal.jahp/2026/14.4.1610.1622>

ISSN (Online) | 2308-2801



Copyright: 2026 by the authors. Licensee ResearchersLinks Ltd, England, UK.

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

INTRODUCTION

Lumpy Skin Disease (LSD) is a highly contagious viral disease of cattle caused by the Lumpy Skin Disease

Virus (Capripoxvirus, family Poxviridae). The disease is characterized by fever, enlarged lymph nodes, and skin nodules, leading to reduced milk production, weight loss, infertility, hide damage, and occasionally mortality.

LSD causes substantial economic losses due to decreased productivity, treatment costs, and trade restrictions. Recent outbreaks across Asia, including India, have highlighted the need for effective surveillance and early diagnosis. However, conventional diagnostic methods are often time-consuming and resource-intensive, particularly in remote farming regions. These challenges have motivated the development of computer vision and artificial intelligence-based approaches for rapid and automated LSD detection.

Recent advances in deep learning have significantly improved the automated detection of LSD from cattle images. [Senthilkumar et al. \(2024\)](#) evaluated several pre-trained convolutional neural network (CNN) architectures for LSD classification under varying imaging conditions and highlighted challenges related to illumination variations, complex backgrounds, and lesion diversity. Similarly, [Saqib et al. \(2024\)](#) demonstrated that deeper CNN architectures can effectively learn discriminative lesion features. But the method achieved moderate classification performance. Practical applications have demonstrated the potential of deep learning systems to enhance disease diagnosis and support more efficient veterinary decision-making processes ([Pal et al., 2025](#)). Their effectiveness is largely attributed to advancements in network design, particularly architectures such as DenseNet, which promote feature reuse through dense connectivity and facilitate efficient information propagation across layers, thereby improving the learning of subtle visual patterns and disease-related features ([Abdullah et al., 2025](#)). Other studies have explored transformer-based and morphology-aware learning approaches to improve the recognition of lesion structures and contextual information in LSD images ([Ullah et al., 2026](#); [Ahmed et al., 2025](#)). Although these methods have reported promising results, most rely primarily on deep feature extraction and focus mainly on comparing network architectures.

Beyond LSD-specific research, deep learning has also been successfully applied to the detection of various livestock diseases. Ensemble learning techniques have been shown to improve classification robustness and generalization by combining the strengths of multiple classifiers ([Khotimah, 2026](#)). Reviews by [Muhindi et al. \(2026\)](#) further demonstrated the growing adoption of CNNs, transfer learning models, and transformer-based approaches for animal disease diagnosis. While these studies provided valuable insights into veterinary image analysis, their findings are not directly tailored to the unique visual characteristics of LSD lesions and therefore require careful adaptation for LSD-specific applications ([Alzubi, 2024](#); [Sahare, 2025](#)).

In addition to deep learning methods, handcrafted texture descriptors remain effective for capturing disease-related

image characteristics. Local Binary Pattern (LBP), introduced by [Song et al. \(2025\)](#), is a widely used texture descriptor known for its computational efficiency and robustness to illumination changes. Its effectiveness has been demonstrated in various medical image classification applications, including disease diagnosis from radiographic and clinical images ([Meravath and Kolluri, 2025](#)). Similarly, Gabor Wavelet features have proven effective for representing texture, orientation, and frequency information in image analysis tasks ([Shafer-Skelton et al., 2026](#)). These properties make Gabor features particularly suitable for characterizing skin lesions and texture irregularities associated with LSD. Despite their success in other image-analysis domains, the combined use of enhanced LBP-based descriptors and Gabor Wavelet features for LSD image classification has received limited attention, as most existing studies focus predominantly on deep learning architectures with relatively little investigation of complementary handcrafted texture representations.

A review of the existing literature reveals several important research gaps. Most LSD detection studies concentrate on comparing deep learning architectures rather than investigating handcrafted texture features that can effectively characterize lesion-specific patterns. Furthermore, limited research has explored the integration of Augmented Local Binary Pattern (ALBP) and multi-scale Gabor Wavelet features to jointly capture local texture variations and directional lesion characteristics. In addition, many existing methods are evaluated using a single dataset, making it difficult to assess their robustness and generalization under diverse imaging conditions.

To address these limitations, this study proposed a hybrid framework that integrated Augmented Local Binary Pattern (ALBP) and patch-wise Gabor Wavelet (GW) features with a Gentle AdaBoost classifier. The block-based ALBP extracted discriminative local texture information while reducing the influence of illumination variations, whereas the Gabor Wavelet features captured multi-scale and multi-orientation texture characteristics, making the framework more robust to variations in lesion size and orientation. The fusion of these complementary descriptors provided a richer representation of LSD lesions and improved classification performance compared with individual feature extraction methods. Specifically, the proposed ALBP descriptor generated a more discriminative representation of local texture patterns than conventional LBP, enabling improved identification of subtle skin lesion characteristics. The block-based feature extraction strategy effectively captured fine-grained texture variations and local structural information in infected skin regions, while the hybrid integration of ALBP and patch-wise Gabor Wavelet features exploited complementary spatial and frequency information to enhance robustness

against illumination changes, viewpoint variations, and lesion heterogeneity. Finally, the Gentle AdaBoost ensemble classifier effectively utilized the fused feature representation to achieve superior detection performance across multiple benchmark datasets. Extensive experiments and ablation studies further demonstrated the effectiveness of the proposed feature descriptors, block-based strategy, and feature fusion in improving the accuracy, robustness, and generalization capability of automated Lumpy Skin Disease detection.

MATERIALS AND METHODS

DATASETS AND IMAGE ACQUISITION

The study was conducted using three publicly available LSD datasets: the Mendeley LSD dataset (Kumar and Shastri, 2022), the Kaggle Lumpy Skin Disease images dataset, and the Veterinary Research LSD dataset. Sample images from the three datasets were presented in Figure 1, and their characteristics were summarized in Table 1. All images were resized to 240 x 240 pixels before feature extraction to ensure consistency. The healthy images exhibited normal skin conditions, whereas infected images contained visible LSD symptoms, including skin nodules and lesions. Ground-truth labels were adopted from the original dataset annotations. Only high-quality images with clear skin visibility and reliable labels were retained, while duplicate, blurred, corrupted, and ambiguously labelled images were excluded.

IMAGE PRE-PROCESSING AND DATA PREPARATION

Figure 2 illustrates the proposed framework, which integrated Augmented Local Binary Pattern (ALBP) and Gabor Wavelet (GW) features with an ensemble classifier for automated Lumpy Skin Disease (LSD) detection in cattle. Initially, healthy and infected cattle images were acquired, resized to a uniform resolution, and divided into training (80%) and testing (20%) sets. ALBP histograms were extracted from the training images to represent local texture characteristics, while GW features captured directional patterns, including lesion boundaries and skin irregularities. The extracted ALBP and GW features were concatenated into a unified feature vector to form the training database. During testing, the same feature

extraction procedure was applied, and the resulting feature vectors were compared with the trained model to classify images as healthy or LSD infected.



Figure 1: Sample images from (a) Mendeley , (b) Kaggle, and (c) Veterinary Research LSD datasets.

The conventional Local Binary Pattern (LBP) method proposed by Song et al. (2025), shown in Figure 3a, encoded pixel neighbourhoods into binary patterns and generated texture histograms. To improve its discriminative capability, the proposed ALBP approach, illustrated in Figure 3b, partitioned each image into non-overlapping blocks, which were further divided into overlapping (4 × 4) sub-blocks. Row-sum differences from overlapping (2 × 2) windows were computed to produce a (3 × 3) representation, and the average value replaced the centre pixel. Binary encoding was then performed by comparing

Table 1: Overview of lumpy skin disease (LSD) image datasets.

Dataset name	Total images	Healthy	LSD - infected	Image size	Key characteristics
Mendeley LSD dataset (Kumar et al., 2022)	1024	700	324	(256 × 256)	Includes multiple breeds (Santa Gertrudis, Brahman, Guzerat, and Yak); with diverse poses, lighting, and perspectives.
Kaggle LSD dataset	8223	4520	3703	(640 × 640)	Large and diverse LSD image dataset;
Veterinary Research LSD dataset	1023	478	545	(256 × 256)	Real-farm images with variations in cattle breed, age, and disease severity

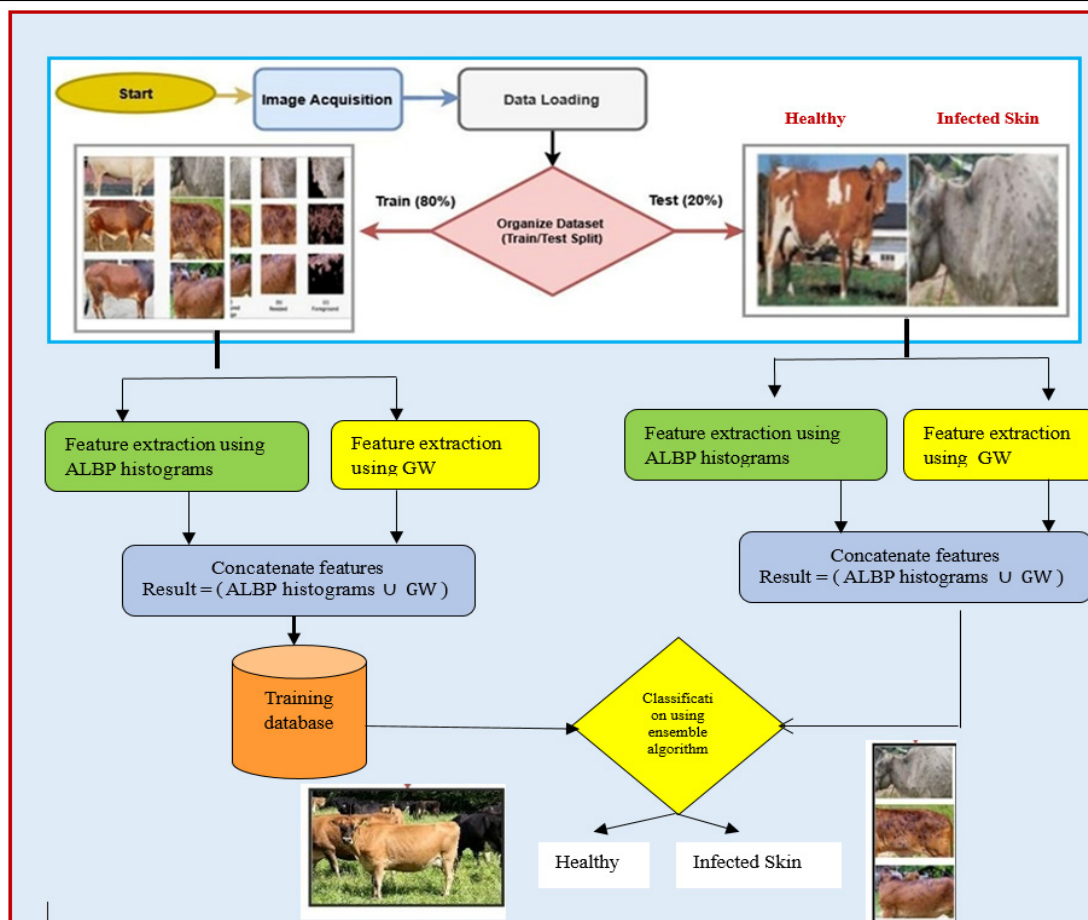


Figure 2: Proposed framework for LSD detection using ALBP histograms and GW with ensemble learning.

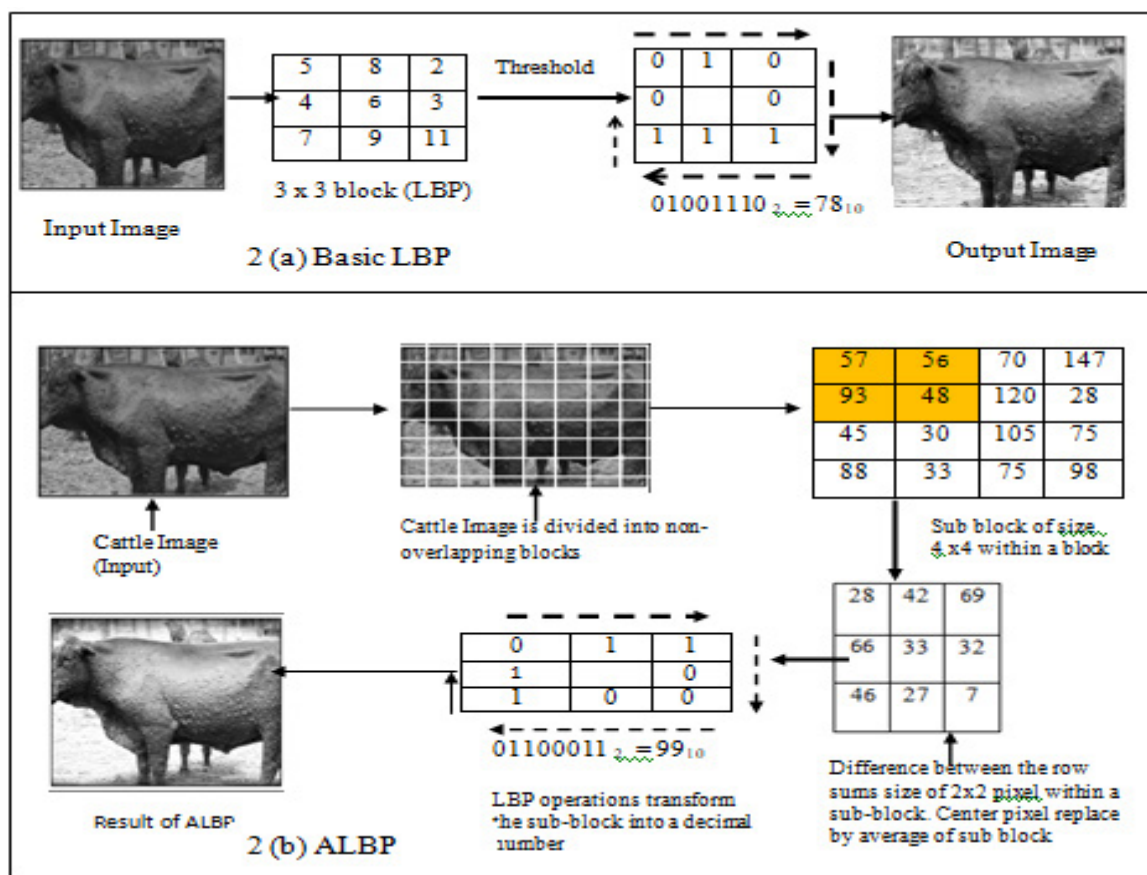


Figure 3: System diagram (a) Local Binary Pattern method (LBP) (b) Amplified Local Binary Pattern method (ALBP).

the centre pixel with its neighbours, followed by histogram generation. Histograms from all blocks were concatenated to produce the final feature vector. This modified descriptor effectively captured fine-grained lesion textures while reducing the influence of noise and illumination changes, thereby improving feature discrimination and higher classification accuracy compared with the conventional LBP method.

FEATURE EXTRACTION USING THE ALBP METHOD

The gray-level cattle image C was divided equally into 64 (8 rows and 8 columns) non-overlapping blocks. Each block was represented as $B(B=1, 2, \dots, (r_1 \times c_1))$. Each block had a size of (30×30) pixels as given below.

$$C_B(aa, bb) = C(aa : aa + bheight - 1, bb : bb + bwidth - 1)$$

where $1 \leq aa \leq r_1 \text{ increment } aa \text{ by } bheight$; $1 \leq bb \leq c_1 \text{ increment } bb \text{ by } bwidth$

Where r_1 and c_1 denoted the number of rows and columns in the cattle image (240×240) pixels respectively and $bheight$ and $bwidth$ were the size of the block height and block width respectively. Each block was again divided into overlapping sub-blocks. It was represented as SB . Generally, each sub-block had a size of (4×4) pixels. The number of sub-blocks was $(m_1 - sb_height + 1) \times (n_1 - sb_width + 1)$ where m_1 and n_1 were the number of rows and columns in each block respectively and sb_height and sb_width were the height and width of the sub-block respectively as given below.

$$C1_{B,SB}(a_1, b_1) = C_B(a_1 : a_1 + sb_height - 1, b_1 : b_1 + sb_width - 1)$$

$1 \leq a_1 \leq m_1 - sb_height + 1$; $1 \leq b_1 \leq n_1 - sb_width + 1$

The ALBP was defined by a binary coding function to obtain the difference between the row sums of each overlapping window size (a_p, b_p) of (2×2) pixels within a sub-block (a_p, b_p) of (4×4) pixels as follows:

Let M represent the matrix defined as follows:

$$M = C1_{B,SB}(a_1, b_1) \quad S(k_x, k_y) = \sum_{a_2=k_x}^{a_2+1} M(k_x, a_2) - \sum_{b_2=k_y}^{b_2+1} M(k_x+1, b_2)$$

$1 \leq k_x \leq sb_height - 1$; $1 \leq k_y \leq sb_width - 1$

Where; $S(k_x, k_y)$ was the difference between the row sum of overlapping window size of (2×2) intensities in a sub-block SB whose size is (4×4) at pixel position (k_x, k_y) . The resultant value was available as (3×3) matrices for each sub-block at pixel position (k_x, k_y) . From that result, the center value was replaced of (3×3) pixels by calculating the average of sub-blocks expressed as:

$$S(2,2) = \frac{1}{k_x * k_y} \sum_{i_2=1}^{k_x} \sum_{j_2=1}^{k_y} S(i_2, j_2)$$

Where; k_x and k_y were the number of rows and columns

in the resulting sub-block (3×3) pixels) respectively. This center value in the sub-block was compared with eight neighbor values. If the center value was less than the neighboring value then the neighboring pixel value was set to 1; otherwise, zero. An 8-bit code was coined, which represents the value in decimal form at each pixel position (a_1, b_1) in the block. The representations of these quantities were as follows:

The value by using the proposed method ALBP was obtained as follows:

$$ALBP(i_1, j_1) = \sum_{n_1=0}^7 T(i_1, j_1) 2^{n_1}$$

where $1 \leq i_1 \leq sb_height - 1$; $1 \leq j_1 \leq sb_width - 1$, $i_1 \neq 2$ and $j_1 \neq 2$

$$T(i_1, j_1) = \begin{cases} 1 & S(i_1, j_1) \geq S(2,2) \\ 0 & \text{else} \end{cases}$$

After obtaining the value using the ALBP method for each pixel associated with a block in the cattle image, a 59-bin histogram was computed to represent the extract the texture features. The histograms of each block in the cattle image $ALBPf$ was defined as follows:

$$ALBPf = \sum_{a_1=b_1} I(ALBP(a, b) = L) \quad 1 \leq a_1 \leq m_1$$

$1 \leq b_1 \leq n_1$; $1 \leq L \leq 59$

Where L is the number of bins for the values produced by the ALBP operator.

$$I(A) = \begin{cases} 1 & A \text{ is true} \\ 0 & A \text{ is false} \end{cases}$$

The $ALBPf$ histograms which are extracted from all blocks were concatenated into a single feature. As a result $ALBPf$ = number of blocks $\times$ histogram bins $((8 \times 8 \times L) = 3776)$ was obtained from each cattle image. The $ALBPf$ histograms contained information about the description of the local micro-patterns such as edges, spots and flat areas over the whole image. Hence, it was used to statistically describe image characteristics. Similarly, the differences between the column sums and diagonal sums were calculated within a sub-block.

Figure 4 illustrates that each cattle image was divided into non-overlapping patches. Texture features were extracted from each patch using the Gabor wavelet approach (Shafer-Skelton *et al.*, 2026) for effective texture analysis. Each patch was convolved with a set of Gabor kernels at multiple orientations and scales. This process enhanced directional texture patterns such as wrinkles, spots, and lesion boundaries present on the animal's skin. The resulting output, commonly referred to as the Gabor magnitude response, emphasized high-frequency components such

as edges and irregular patterns while suppressing uniform regions. Finally, the extracted local texture features from all patches were concatenated into a single feature vector for further processing.

FEATURE EXTRACTION USING PATCH-WISE GABOR WAVELET

Each cattle image I was divided into non-overlapping patches denoted by P ($P=1, 2, \dots, (m \times n)$). The m and n denote the numbers of patches arranged in rows and columns respectively. The total number of patches was $m \times n$. Typically, the m_i and n_i denoted the row and column dimensions of each patch size (i.e., pixels) respectively.

$$I_p(a, b) = I(a : a + m_i, b : b + n_i)$$

Where; $a = 1 : r_1$ step by m_i ; $b = 1 : c_1$ step by n_i

Where r_1 and c_1 were numbers of rows and columns in the cattle image respectively, m_i and n_i were the row and column of each patch size, respectively.

$$I_{G,p}(x, y) = I_p(x, y) * g(x, y)$$

Where; $I_p(x, y)$ represented each patch of the cattle image and $g(x, y)$ denotes the two-dimensional (2D) Gabor Kernel. The symbol $*$ denotes convolution. The magnitude was then computed as follows:

$$g(x, y) = e^{-\frac{x^2 + y^2}{2\sigma^2}} \cos(2\pi f x + \theta)$$

Where; $g(x, y)$ was the Gabor filter response, σ denotes the scale, f represents the frequency and θ represents the orientation, I_G captured texture and directional characteristics of LSD lesions. The features extracted from all patches were concatenated into a single feature

vector as GW. This process yielded a feature vector of size expressed as follows:

$$GW = \text{number of patches} \times \text{number of scales} \times \text{number of orientations}$$

This magnitude image provided a clearer representation of texture variations, making it highly effective for identifying abnormal skin patterns in cattle.

ENSEMBLE LEARNING FOR CLASSIFICATION

Features were extracted from each image using both ALBP and Gabor wavelet techniques. These extracted feature vectors were concatenated to form a combined representation, expressed as follows:

$$\text{Result} = \text{ALBPf} \cup \text{GW}$$

Where; $\cup$ denoted the concatenation operation. Consequently, the final representation of each image consisted of a high-dimensional feature vector determined by the number of blocks, histogram bins, patches, scales, and orientations. The extracted features were subsequently provided as input to an ensemble learning model for classification.

The boosting algorithm, originally proposed by Khotimah (2026) for object detection, was employed because of its ability to achieve a low false-positive rate. A key advantage of the boosting approach was its ability to combine multiple weak learners to construct a strong classifier while reducing redundancy in high-dimensional feature spaces, thereby improving computational efficiency. However, boosting methods were sensitive to noisy data and outliers. In this study, three AdaBoost variants Real AdaBoost (RA), Gentle AdaBoost (GA), and Modest AdaBoost (MA) were employed to classify cattle skin images into two categories: healthy and infected.

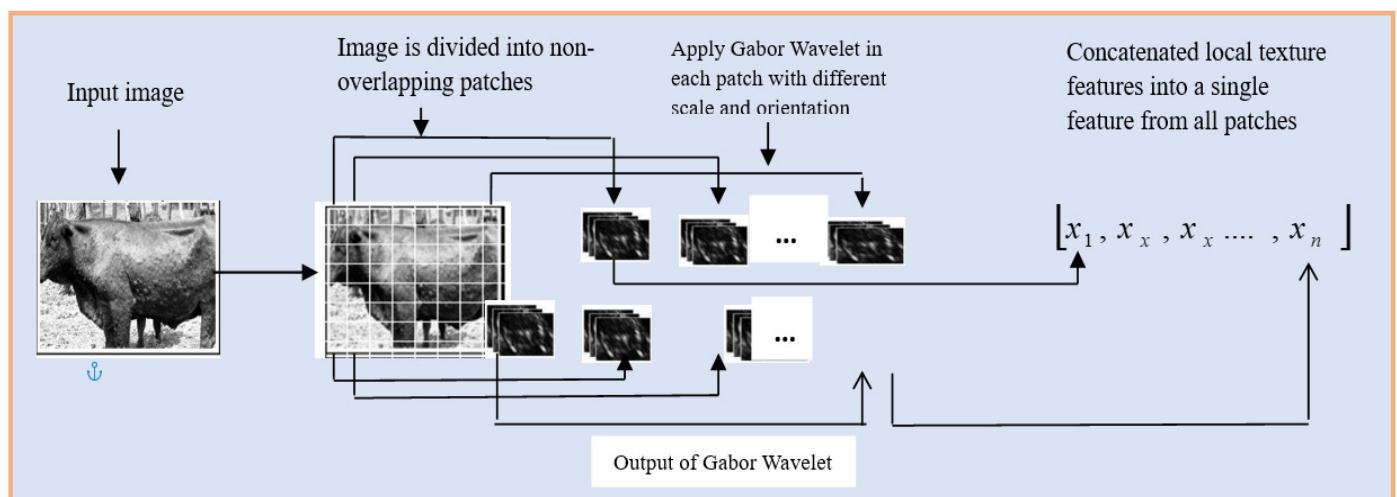


Figure 4: System diagram for Patch-Wise Gabor wavelet feature extraction method.

EXPERIMENTAL SETUP

The experiments were conducted using MATLAB R2017 on a personal computer equipped with an Intel Core i5 processor (3.20 GHz) and 8 GB of RAM. The proposed framework was evaluated using an 80:20 training–testing split. Feature vectors were normalized using min–max normalization before classification. The AdaBoost classifier was configured with 500 weak learners, a learning rate of 0.1, and 100 boosting iterations. To improve robustness and address class imbalance, data augmentation techniques, including rotation, and scaling, together with class weighting, were applied during training. The use of three independent datasets increased data diversity and reduced dataset bias, enabling comprehensive evaluation under varying imaging conditions, class distributions, cattle breeds, and disease stages. This experimental design improved the generalization and practical applicability of the proposed framework in real-world livestock disease detection.

PERFORMANCE OF ALBP FEATURES

The ALBP features effectively captured local texture variations and micro-patterns in cattle skin, helping to distinguish the irregular textural characteristics of LSD lesions from healthy skin. The results demonstrated that ALBP provided useful discriminative information for identifying LSD-infected cattle.

PERFORMANCE ANALYSIS ON DIFFERENT SIZES OF BLOCK IN ALBP

The results presented in Table 2 demonstrate that the number of blocks and block size significantly influenced classification performance. The 36-block configuration (40×40 pixels) achieved accuracies ranging from 90% to 92.7%, whereas the 64-block configuration (30×30 pixels) improved accuracy to 91–95%, producing the best performance across all three datasets. Increasing the partition to 100 blocks (24×24 pixels) resulted in a slight reduction in accuracy, indicating that the 64-block configuration provided the optimal balance between capturing discriminative local texture information and computational efficiency for classifying healthy and LSD-infected cattle skin.

Table 2: Detection accuracy of LSD using different sizes of block.

Number of blocks	Each block size (in Pixels)	Accuracy (%)*								
		Mendeley dataset			Kaggle dataset			Veterinary research LSD dataset		
		RA	GA	MA	RA	GA	MA	RA	GA	MA
36 (6 rows, 6 columns)	(40×40)	90	92	89	92	94	92	90–93	92	89
64 (8 rows, 8 columns)	(30×30)	91	93	91	94	95	93	92	94	91
100 (10 rows, 10 columns)	(24×24)	89	90	88	92	94	92	90	93	91

* Real AdaBoost denoted as RA, Gentle AdaBoost denoted as GA, and Modest AdaBoost denoted as MA.

Table 3: Detection of LSD using different sizes of sub-block.

Different sub-block size	Different window size		Recognition rate (%)*								
			Mendeley dataset			Kaggle dataset			Veterinary research LSD dataset		
			RA	GA	MA	RA	GA	MA	RA	GA	MA
Raw pixel	---	----	88	89	89	90	90	89	91	92	90
(3×3) LBP [#]	---	-----	90	91	90	91	92	90	90	92	91
(4 × 4) ALBP	(2 × 2)	Row sums	92	93.5	91	92	95	92	91	94	91
		Column sums	91	92	92	90	90	91	91	92	92
		Diagonal sums	91	92	91	92	92	91	91	92	92
(5 × 5) ALBP	(3 × 3)	Row sums	90	91	90	92	91	92	90	92	92
		Column sums	92	92	91	91	92	91	92	92	90
		Diagonal sums	91	92	89	91	92	92	90	92	91
(6 × 6) ALBP	(4 × 4)	Row sums	91	92	91	91	92	92	91	92	92
		Column sums	91	92	88	90	92	92	91	92	92
		Diagonal sums	91	92	90	92	92	90	90	92	92
(7 × 7) ALBP	(5 × 5)	Row sums	90	91	90	90	92	91	92	92	90
		Column sums	89	90	89	91	91	92	90	92	91
		Diagonal sums	90	92	91	92	90	91	91	91	90

* Real AdaBoost denoted as RA, Gentle AdaBoost denoted as GA, and Modest AdaBoost denoted as MA. [#] Song *et al.* (2025).

Table 4: Detection of LSD using different sizes of Gabor patch.

Number of patches	Each patch size (Pixels)	Accuracy (%)		
		Mendeley dataset	Kaggle dataset	Veterinary research LSD dataset
Gabor Wavelet – without patches*		90	91	91
16 (arranged in 4 rows, 4 columns)	(64 × 64)	92.5	92.7	92
64 (arranged in 8 rows, 8 columns)	(32 × 32)	94.5	94	95.8
256 (arranged in 16 rows, 16 columns)	(16 × 16)	94	93	92.3

*Shafer-Skelton *et al.* (2026).

PERFORMANCE ANALYSIS ON DIFFERENT SIZES OF SUB-BLOCK IN ALBP

The performance of the proposed ALBP descriptor was evaluated using different sub-block sizes. Three ALBP variants based on row-wise, column-wise, and diagonal intensity differences were investigated using sub-block sizes of (3 × 3), (4 × 4), (5 × 5), (6 × 6) and (7 × 7). The (3 × 3) sub-block corresponded to the conventional LBP. Larger sub-blocks were reduced to a (3 × 3) representation by computing intensity differences over overlapping (2 × 2) windows, after which the standard LBP encoding was applied. Histograms generated from all image blocks were concatenated to form a unified feature vector and subsequently classified using ensemble AdaBoost techniques. The proposed method was independently evaluated on the three datasets, and the results are presented in Table 3. Among all configurations, the ALBP descriptor generated from (4 × 4) sub-blocks using row-wise differences with the Gentle AdaBoost classifier consistently achieved the highest classification performance across all datasets.

PERFORMANCE OF GABOR WAVELET FEATURES

Gabor Wavelet (GW) features effectively captured the directional, frequency, and structural variations of cattle skin lesions. The results demonstrated that Gabor Wavelet features provided useful discriminative information for distinguishing LSD-infected cattle from healthy cattle.

PERFORMANCE ANALYSIS ON DIFFERENT SIZES OF GABOR PATCH

The proposed model was evaluated using different numbers of image patches, with Gabor filters applied to each patch for texture feature extraction. As shown in Table 4, the 64-patch configuration (8 × 8 grid, 32 × 32 pixels) achieved the highest accuracies of 94.5%, 94.0%, and 95.8% on the Mendeley, Kaggle, and Veterinary Research LSD datasets, respectively. It also outperformed the Gabor Wavelet approach without patches reported by Shafer-Skelton *et al.* (2026), which achieved 90%, 91%, and 91%. Therefore, the 64-patch configuration was selected for subsequent experiments.

PERFORMANCE ANALYSIS OF DIFFERENT GABOR SCALE AND GABOR ORIENTATIONS

In these experiments, the orientation and scale parameters of the Gabor filter play a crucial role in determining the effectiveness of texture-based feature extraction. A comparative evaluation was conducted using different orientation sets, including 2 orientations (0°, 90°), 4 orientations (−45°, 0°, 45°, 90°), 6 orientations (−45°, −22.5°, 0°, 22.5°, 45°, 90°), and 8 orientations (−67.5°, −45°, −22.5°, 0°, 22.5°, 45°, 67.5°, 90°), while maintaining a fixed scale value of eight. The experimental results across three datasets were presented in Table 5 using a variant ensemble classifier.

Table 5: Detection of LSD using four sets of orientation.

Number of orientations	Accuracy (%)								
	Three datasets*								
	Mendeley dataset			Kaggle dataset			Veterinary research dataset		
	RA	GA	MA	RA	GA	MA	RA	GA	MA
2	90	93	88	90	91	90	91	92	90
4	92	94.5	93	92	94	93	92	95.8	94
6	93	93	91	90	91	89	92	93	92
8	92	93	90	88	89	97	90	93	92

* Real AdaBoost denoted as RA, Gentle AdaBoost denoted as GA, and Modest AdaBoost denoted as MA.

Table 6: Detection of LSD using four sets of scales.

Number of scale	Accuracy (%)								
	Three datasets*								
	Mendeley dataset			Kaggle dataset			Veterinary research dataset		
	RA	GA	MA	RA	GA	MA	RA	GA	MA
4	90	93	88	86	88	87	89	91	86
6	91	92	90	89	90	87	90	92	89
8	93	94.5	91	91	94	90	93	95	92
10	92	93	90	89	90	88	91	92	91

* Real AdaBoost denoted as RA, Gentle AdaBoost denoted as GA, and Modest AdaBoost denoted as MA.

Table 7: Performance comparison of ALBP, Gabor, and combined ALBP + GW features with Gentle AdaBoost.

Model Name	Accuracy	F1-Score	Recall	Precision	Dataset
ALBP + Gentle AdaBoost	0.94	0.91	0.93	0.89	Mendeley dataset
GW + Gentle AdaBoost	0.95	0.94	0.94	0.94	Mendeley dataset
ALBP + GW + Gentle AdaBoost (Proposed)	0.98	0.96	0.95	0.96	Mendeley dataset
ALBP + Gentle AdaBoost	0.95	0.93	0.94	0.92	Kaggle dataset
GW + Gentle AdaBoost	0.96	0.94	0.94	0.93	Kaggle dataset
ALBP + GW + Gentle AdaBoost (Proposed)	0.97	0.96	0.95	0.96	Kaggle dataset
ALBP + Gentle AdaBoost	0.94	0.92	0.93	0.92	Veterinary Research LSD dataset
GW + Gentle AdaBoost	0.96	0.93	0.93	0.93	Veterinary Research LSD dataset
ALBP + GW + Gentle AdaBoost (Proposed)	0.98	0.98	0.98	0.99	Veterinary Research LSD dataset

Furthermore, the impact of varying scale parameters was analyzed by fixing the number of orientations at four and evaluating scale ranges of (5:2:11), (5:2:15), (5:2:19), and (5:2:23), corresponding to 4, 6, 8, and 10 scales, respectively. The results, shown in Table 6 using the same variant ensemble classifier, indicate that this configuration was effective in distinguishing between healthy and infected skin across all datasets. From Tables 5 and 6, it was observed that the highest classification accuracy was achieved using 4 orientations and 8 scales, with the GA classifier demonstrating superior performance compared to other scale–orientation combinations and AdaBoost classifiers across all three datasets. The Gabor feature extraction process produced a feature vector of size 32, derived from 8 scales and 4 orientations.

PERFORMANCE COMPARISON OF ALBP, GABOR, AND COMBINED ALBP + GW FEATURES WITH DIFFERENT ADABOOST CLASSIFIERS

The Receiver Operating Characteristic (ROC) curves were plotted based on the results obtained using the ALBP histograms alone, GW alone, and combined ALBP and GW with Adaboost variants classifier such as Real AdaBoost (RA), Gentle AdaBoost (GA), and Modest AdaBoost (MA), to classify cattle skin images as either healthy or infected. These evaluations were performed on the three datasets and the corresponding results are presented in Figure 5. The analysis of GA yielded higher classification rate than RA and MA. Hence, GA was selected as the classification algorithm for our system.

The ROC curve illustrates the trade-off between the FPR and the TPR (recognition rate). The results indicate that the proposed ALBP + GW with the GA model achieved superior LSD detection performance. This combination demonstrated a high recognition rate while maintaining a low FPR across all datasets.

EVALUATION OF LSD DETECTION PERFORMANCE

The models were evaluated using accuracy, F1-score, recall, and precision across three LSD datasets, as shown in Table 7. The combined ALBP–GW features with Gentle AdaBoost consistently outperformed the individual

ALBP and GW features, achieving accuracies of 0.98, 0.97, and 0.98 on the Mendeley, Kaggle, and Veterinary Research datasets, respectively. These results demonstrate the effectiveness of combining complementary texture and frequency-domain features.

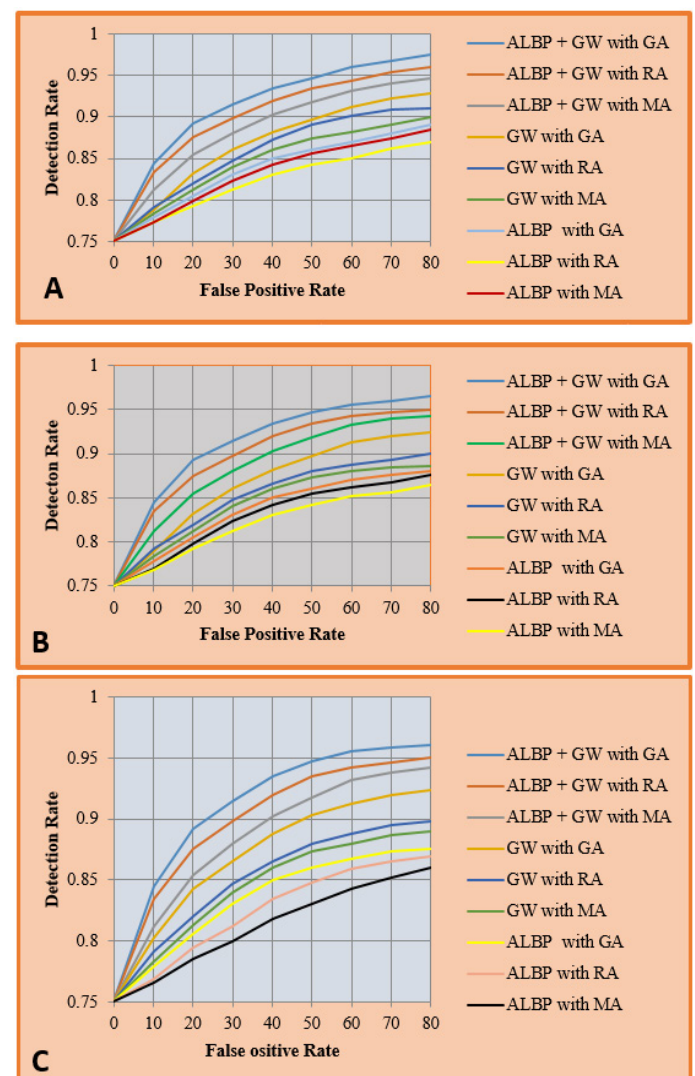


Figure 5: ROC curves comparing the detection performance of ALBP alone, Gabor Wavelet (GW) alone, and the integrated ALBP + GW features using different AdaBoost classifier variants: Real AdaBoost (RA), Gentle AdaBoost (GA), and Modest AdaBoost (MA). Where (a) Mendeley (b) Kaggle (c) Veterinary Research datasets.

For the Veterinary Research dataset, which contains 1,023 cattle skin images comprising 478 healthy and 545 infected samples, the confusion matrix in Table 8 shows that 536 infected (TP) and 470 healthy (TN) images were correctly classified, while 9 infected (FN) and 8 healthy (FP) images were misclassified. These results demonstrate the effectiveness of the proposed model in distinguishing between healthy and LSD-infected cattle images.

Table 8: Confusion matrix for veterinary research LSD dataset.

	Predicted infected	Predicted healthy
Actual infected	536 (TP)	9 (FN)
Actual healthy	8 (FP)	470 (TN)

COMPARISON WITH EXISTING LSD DETECTION METHODS

Table 9 compares the proposed framework with existing LSD detection approaches using the same 80:20 training-testing protocol, datasets, preprocessing steps, and evaluation metrics, providing a consistent basis for comparison. The compared methods include several deep learning approaches, which achieved accuracies ranging from 90% to 95%, whereas the proposed ALBP + GW with Gentle AdaBoost achieved accuracies of 98%, 97%, and 98% on the Mendeley, Kaggle, and Veterinary Research datasets, respectively. The proposed framework also required only 22, 23, and 24 s for the Mendeley,

Kaggle, and Veterinary Research datasets, respectively, demonstrating competitive computational efficiency. Overall, the results indicate that the proposed feature-fusion and ensemble-learning strategy provides a favorable balance between classification accuracy and computational cost compared with existing LSD detection methods.

CROSS-VALIDATION AND STATISTICAL ANALYSIS

The framework was evaluated using 10-fold cross-validation, achieving average accuracies of 98.5%, 97.45%, and 98.7% on the Mendeley, Kaggle, and Veterinary Research LSD datasets, respectively. The 10-fold cross-validation accuracy was higher than the accuracy obtained from the single 80:20 train-test split; this difference reflects the use of different data-partitioning and evaluation protocols rather than the use of the independent test set during model training.

For the 10-fold cross-validation analysis, ten fold-wise accuracy values were obtained for each dataset. These ten values were treated as repeated evaluation units for statistical comparison. The paired t-test was used to compare the fold-wise accuracies of the proposed ALBP-GW framework and the individual-feature approaches using identical folds. One-way ANOVA was used to assess differences among the mean performances of the evaluated methods, while McNemar’s test was applied to paired classification outcomes obtained from the same evaluation samples. Statistical significance was assessed at $p < 0.05$.

Table 9: Comparison of existing approaches with proposed methodology where A represents accuracy.

Authors	Year	Model / Technique	Classifier	A for accuracy (%) S for seconds					
				Mendeley		Kaggle		Veterinary research	
				A	S	A	S	A	S
Saqib <i>et al.</i>	2024	Deep learning	MobileNetV2 + RMSProp	92	24	91	25	92	26
Senthilkumar <i>et al.</i> ,	2024	Transfer learning	MobileNetV2	91	24	90	25	93	25
AlZubi <i>et al.</i> ,	2024	Deep Learning	Advanced CNN	92	25	91	26	92	24
Sahare	2025	Deep Learning	CNN	91	21	91	23	90	24
Abdullah <i>et al.</i> ,	2025	Transfer learning	DenseNet121	92	23	92	22	91	24
Pal <i>et al.</i> ,	2025	Deep learning ensemble	ViT + ConvMixer	93	23	93	24	94	24
Gouda <i>et al.</i> ,	2025	Ensemble ML + resampling	RF, AdaBoost, GBoost, XGBoost	90	25	91	25	90	26
Meravath <i>et al.</i> ,	2025	Hybrid deep learning + attention	Muti-scale hybrid model	92	24	90	26	90	26
Muhindi <i>et al.</i> ,	2026	Swin Transformer Tiny	CNN	92	26	91	27	91	27
Ayon <i>et al.</i> ,	2026	Deep learning ensemble	VGG16 + ResNet50 + InceptionV3	96	31	96	29	97	29
Ahmed <i>et al.</i> ,	2025	Morphological priors + local texture refinement	YOLO + EfficientNet	95	24	95	25	96	25
Ubaidullah <i>et al.</i> ,	2026	Lesion detection + deep features	YOLOv11 + EfficientNet	94	26	96	26	96	27
Ullah <i>et al.</i> ,	2026	Deep learning	Vision Transformer (ViT)	94	25	95	24	95	26
Khotimah <i>et al.</i> ,	2026	Ensemble deep learning + L2 regularization	Weighted ensemble CNN	95	26	96	26	95	25
Senussi <i>et al.</i> ,	2026	Multi-scale deep learning	ConvNeXtLSD	96	27	96	25	97	25
Our Proposed	2026	ALBP + GW	Gentle Adaboost	98	22	97	23	98	24

Statistical analysis further supported the robustness of the proposed framework. Cohen's kappa coefficient of 0.95 (95% CI: 0.94–0.98) indicated almost perfect agreement between the predicted and reference classifications. The McNemar's test, paired t-test, and one-way ANOVA indicated statistically significant differences in the observed performance ($p < 0.05$). Overall, the proposed framework demonstrated improved performance compared with the individual-feature approaches across the three datasets.

DISCUSSION

This study presented an automated LSD detection framework integrating Augmented Local Binary Pattern (ALBP) and Gabor Wavelet (GW) features with Gentle AdaBoost. As shown in Table 9, the proposed framework achieved accuracies of 98%, 97%, and 98% on the Mendeley, Kaggle, and Veterinary Research LSD datasets, respectively. The existing methods achieved accuracies ranging from 90% to 97%. Ayon *et al.* (2026), using a VGG16 + ResNet50 + InceptionV3 ensemble, and Senussi *et al.* (2026), using ConvNeXtLSD, achieved the highest performance among the compared methods, with accuracies of 96–97%. However, deep learning and transfer-learning approaches may depend strongly on the quality, diversity, and size of the training data, which may limit their ability to generalize across variations in lesion appearance, illumination, background, and image acquisition conditions. This may explain the comparatively lower performance of MobileNetV2 with RMSProp by Saqib *et al.* (2024), MobileNetV2 transfer learning by Senthilkumar *et al.* (2024), advanced CNN by Al-Zubi (2024), CNN by Sahare (2025), and DenseNet121 by Abdullah *et al.* (2025).

Similarly, ViT + ConvMixer by Pal *et al.* (2025) and the multi-scale hybrid model by Meravath and Kolluri (2025) combined multiple feature representations, which can increase model complexity and may require more representative training samples to learn robust features. The VGG16 + ResNet50 + InceptionV3 ensemble of Ayon *et al.* (2026), although achieving strong performance, involves multiple deep networks and therefore has greater architectural complexity. Likewise, YOLO + EfficientNet by Ahmed *et al.* (2025), YOLOv11 + EfficientNet by Ubaidullah *et al.* (2026), and the weighted ensemble CNN with L2 regularization by Khotimah (2026) employ multiple learning components, potentially increasing computational requirements and sensitivity to training configurations. The Swin Transformer-Tiny by Muhindi *et al.* (2026) and Vision Transformer (ViT) by Ullah *et al.* (2026) rely on attention-based global representations and may require sufficiently diverse training data to capture variations in LSD lesions effectively. The ensemble

machine-learning approach of Gouda and Abdallah (2025), using RF, AdaBoost, Gradient Boosting, and XGBoost with resampling, may also be influenced by feature quality and resampling strategies, which can affect generalization across datasets.

In contrast, the proposed ALBP–GW framework combines complementary local texture and directional frequency information. ALBP captures fine-grained local variations in lesion texture, while GW characterizes directional and frequency-dependent patterns. This combination enables the framework to represent irregular LSD lesion characteristics more effectively without relying on multiple deep architectures. Consequently, the proposed method achieved consistently strong performance across all three datasets while maintaining execution times of 22, 23, and 24 s, respectively. These results indicate that the proposed ALBP–GW framework provides a favorable balance between detection accuracy, feature representation, and computational efficiency under the experimental conditions considered.

CONCLUSIONS

An automated image-based framework for the early detection of Lumpy Skin Disease (LSD) in cattle was proposed by integrating Augmented Local Binary Pattern (ALBP) and Gabor Wavelet (GW) feature extraction method with an ensemble learning-based classification strategy. The proposed ALBP–GW framework was designed to exploit complementary visual characteristics of LSD lesions: ALBP effectively characterizes local texture variations and micro-patterns, while GW captures directional, frequency-dependent, and structural information associated with skin lesions, nodules, and surface irregularities. By fusing these complementary descriptors, the proposed method provided a more informative and discriminative representation of affected and healthy cattle images than relying on a single feature descriptor. The integration of the fused ALBP–GW representation with ensemble classifiers further strengthens the classification capability by combining the decision-making characteristics of multiple learners and improving the robustness of the prediction process. Experimental evaluation on three independent LSD datasets Mendeley, Kaggle, and Veterinary Research achieved classification accuracies of 98.0%, 97.0%, and 98.0%, respectively. The consistently high performance across datasets demonstrated the effectiveness of the proposed feature-fusion and ensemble-learning strategy under the evaluated experimental conditions. These results indicated that the proposed framework could effectively distinguish LSD-related visual patterns while maintaining stable classification performance across datasets with

different image characteristics.

The execution-time results further demonstrated that the proposed approach maintains competitive computational efficiency. The proposed framework required 22, 23, and 24 seconds for the Mendeley, Kaggle, and Veterinary Research datasets, respectively. These values are comparable to or lower than several deep learning-based approaches that achieved lower classification accuracies. Therefore, the proposed ALBP–GW with Gentle AdaBoost provides a favorable balance between classification accuracy and computational efficiency, making it a promising candidate for computer-assisted LSD screening. A key strength of the proposed approach is its ability to achieve high classification performance using computationally efficient handcrafted feature descriptors combined with ensemble learning, thereby providing a potentially cost-effective alternative to computationally intensive end-to-end deep learning approaches.

LIMITATIONS AND FUTURE WORK

Despite its promising performance, the framework was evaluated under specific experimental conditions and may be affected by variations in cattle breed, age, skin pigmentation, illumination, occlusion, camera viewpoint, disease severity, and environmental conditions. The availability of diverse real-world farm images was also limited, which may affect the generalizability of the framework across different farms and surveillance environments.

Future work will focus on expanding the framework using larger and more diverse real-world farm datasets and conducting cross-farm and cross-camera validation. Further investigations will include comparisons with state-of-the-art deep-learning and vision-based models, explainable prediction mechanisms, and deployment on mobile, edge, and real-time surveillance platforms. These developments could support the integration of the framework into automated livestock health-monitoring systems, potentially enabling earlier disease screening and facilitating timely veterinary intervention.

ACKNOWLEDGMENTS

All authors are thankful to the Koneru Lakshmaiah Education Foundation for supporting this work and providing valuable insights.

NOVELTY STATEMENT

The proposed study introduced a hybrid handcrafted feature framework that integrated Augmented Local Binary Pattern (ALBP) and Gabor Wavelet (GW)

descriptors for automated Lumpy Skin Disease detection in cattle. A novel ALBP descriptor based on overlapping sub-blocks with row-wise intensity differences was developed to capture discriminative lesion textures while improving robustness to noise and illumination variations. The fused ALBP–GW features, combined with the Gentle AdaBoost classifier, achieved superior accuracy and computational efficiency compared with existing deep learning and hybrid approaches. The framework was further validated on three independent public datasets, demonstrating strong generalization and suitability for real-world livestock disease monitoring.

AUTHOR'S CONTRIBUTION

IRPS: Conceptualization, experimental design, data analysis, manuscript writing, and corresponding author. YRAR, RC: Conducted the experiment, sample collection, and laboratory analyses. VS, DM and SA: Statistical analysis, interpretation of results, and critical revision of the manuscript. All authors read and approved the final manuscript.

GENERATIVE AI AND AI ASSISTED TECHNOLOGY STATEMENT

The authors declare that no generative AI and AI assisted technology was used in the creation of this manuscript.

CONFLICT OF INTEREST

The authors have declared no conflict of interest.

REFERENCES

- Abdullah W, Tanwar S, Abouhawwash M (2025). Deep learning-based detection of lumpy skin disease in livestock using CNNs. *Sustain. Machine Intell. J.*, 11: 1–10. <https://doi.org/10.61356/SMIJ.2025.11515>
- Ahmed MJ, Chalise R, Bhandari P (2025). Lumpy Skin Disease in Cattle and Buffalo in Asian Countries: A Systematic Review and Meta-Analysis. *Veterinary Medicine and Science*, 11(5): e70607. <https://doi.org/10.1002/vms3.70607>
- Al-Zubi A (2024). Lumpy skin disease detection in cattle by a robust approach using advanced convolutional neural networks. *Indian J. Anim. Res.*, 58(12): 2146–2153. <https://doi.org/10.18805/IJAR.BF-1793>
- Ayon NB, Hasib A, Ahmed MF, Rahman MS (2026). Simultaneous detection of LSD and FMD in cattle using ensemble deep learning. *arXiv preprint arXiv: 2601.12889*.
- Gouda HF, Abdallah FDM (2025). Comparative performance of bagging and boosting ensemble models for predicting lumpy skin disease with multiclass-imbalanced data. *Sci. Rep.*, 15(1): 39373. <https://doi.org/10.1038/s41598-025-23846-7>
- Khotimah BK (2026). A robust ensemble deep learning model for lumpy skin disease identification. *Eng. Technol. Appl. Sci. Res.*, 16(1): 31285–31293. <https://doi.org/10.48084/etasr.14823>

- Kumar S, Shastri (2022). Lumpy skin images dataset. Mendeley Data, 1. Available at: <https://data.mendeley.com/datasets/w36hpf86j2/1>.
- Meravath C, Kolluri R (2025). A hybrid deep learning framework with attention and multi-scale features for early detection of lumpy skin disease in cattle. IEEE 9th International Conference on Information and Communication Technology (CICT). DOI: [10.1109/CICT67193.2025.11399184](https://doi.org/10.1109/CICT67193.2025.11399184).
- Muhindi G, Wambugu MG, Oirere A (2026). A survey of deep learning methods for detection of lumpy skin disease. Int. J. Technol. Emerg. Sci., 6(1): 1–10.
- Pal M, Behera S, Mohapatra R (2025). Implementation of a deep learning system for detection and classification of lumpy skin disease in cattle. Vet. Med. Sci., 11(6).
- Sahare D (2025). Detection of lumpy skin disease in cattle using convolutional neural networks (CNN): A review. Int. J. Res. Appl. Sci. Eng. Technol., 13(4): 101–106. <https://doi.org/10.22214/ijraset.2025.68192>
- Saqib SM, Iqbal M, Ben Othman MT, Shahazad T, Ghadi YY (2024). Lumpy skin disease diagnosis in cattle: a deep learning approach optimized with RMSProp and MobileNetV2. PLoS One, 19(8): e0302862. <https://doi.org/10.1371/journal.pone.0302862>
- Senthilkumar C, Sindhu C, Vadivu G, Neethirajan S (2024). Early detection of lumpy skin disease in cattle using deep learning a comparative analysis of pretrained models. Veterinary Sciences, 11(10): 510. <https://doi.org/10.3390/vetsci11100510>
- Senussi MF, Heikal AS, Abdelbasset AG (2026). Robust multi-class lumpy skin disease diagnosis for practical livestock applications. Sci. Rep., 16: 26662. <https://doi.org/10.1038/s41598-026-66229-2>
- Shafer-Skelton A, Brady TF, Serences JT (2026). A 2D Gabor-wavelet baseline model out-performs a 3D surface model in scene-responsive cortex. PLoS Comput. Biol., 22(2): e1013888. <https://doi.org/10.1371/journal.pcbi.1013888>
- Song Y, Sa J, Luo Y, Zhang Z (2025). A comprehensively improved local binary pattern framework for texture classification. Multimed. Tools Appl., 84: 22043–22068. <https://doi.org/10.1007/s11042-024-19877-3>
- Ubaidullah, Hussain MA, Jafri MR, Khan R, Sandhu M (2026). Adaptive hybrid optimizer based framework for lumpy skin disease identification. arXiv:2601.01807. DOI: [10.48550/arXiv.2601.01807](https://doi.org/10.48550/arXiv.2601.01807)
- Ullah A, Haider A, Rahulamathavan Y, Khokhar MW (2026). A vision transformer model-integrated mobile application for early and accurate detection of lumpy skin disease in cattle. Sci. Rep., 16: 683. <https://doi.org/10.1038/s41598-025-30259-z>