An Automatic Approach for the Classification of Lumpy Skin Disease in Cattle

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Abstract

Lumpy Skin Disease (LSD) presents significant risks and economic challenges to global cattle farming. Effective and accurate classification of LSD is essential for managing the disease and reducing its impacts. Manual diagnosis is time-consuming, labor-intensive, and requires experienced personnel. Automated classification methods provide advantages by reducing labor and improving accuracy. This study proposes an automated algorithm for LSD classification using machine learning. The method uses a carefully curated dataset of images from both LSD-infected cattle and healthy cattle. Inception V3 was employed to extract features from complex lesion patterns in infected cattle images, comparing them to healthy cattle images. Support Vector Machines (SVM) were used to classify the extracted features. The results show the model achieved an 84% accuracy rate, with precision at 80%, recall at 83%, and an F1 score of 82%. These results were compared with other machine learning models, including Logistic Regression, Random Forest, Decision Tree, and AdaBoost. SVM outperformed other models, demonstrating consistent evaluation precision at 0.84. For further enhancement, expanding the dataset with high-quality images and applying advanced machine learning algorithms like Vision Transformers (ViTs), MobileNetV2, and Visual Geometry Group (VGG) could refine automated LSD classification. The aim is to improve disease management practices in the livestock industry through better classification systems.

Keywords: Lumpy Skin Disease, Deep Learning, Feature Extraction, Support Vector Machine (SVM).

1. Introduction

Lumpy Skin Disease (LSD) is a severe viral infection caused by the LSD virus (LSDV), a member of the genus *Capripoxvirus* within the Family *Poxviridae* (Khan et al., 2021; Haider et al., 2024). LSD has a high infection rate, leading to major harmful effects on the cattle farming industry. The disease manifests through two main symptoms: skin nodules accompanied by fever, reduced milk production, and weight loss, which can be fatal in severe cases. The virus is primarily transmitted through insect vectors, such as flies, mosquitoes, and ticks. In Pakistan, LSD has caused significant economic losses and livestock mortality (Khatri et al., 2023). Raising public awareness and implementing control measures are crucial for managing LSD outbreaks, protecting animal health, and ensuring the economic stability of cattle farming. LSD poses a major challenge to global livestock operations, impacting meat quality, milk production, and trade (Akhter et al., 2023). The infection damages cattle skin, and the painful nodules cause significant discomfort to livestock. Timely identification of LSD lesions is crucial for controlling the disease and implementing effective prevention strategies. However, current diagnostic methods rely on human evaluators performing manual visual assessments, which often lead to inconsistent results due to subjective interpretation. While Polymerase Chain Reaction (PCR) tests are useful, their manual handling and inability to differentiate between virus strains highlight the pressing need for automated, standardized diagnostic solutions (Bora et al., 2022).

1.1. Motivation

Given the severe challenges posed by LSD, there is an urgent need for an automated diagnostic method (Ahmad et al., 2023). Such a solution has the potential to transform disease identification and classification, ushering in a new era of improved performance and accuracy in livestock management. This study aims to bridge traditional diagnostic methods with machine learning technology to develop better diagnostic systems for LSD (Tuncel et al., 2023). An automated system would enable faster diagnosis while ensuring precise and standardized evaluations. This innovation enhances disease control and protects livestock farmers' income, as early and accurate diagnosis is crucial to minimize the financial impact of LSD outbreaks (Foster, 2023). The development of a computerized diagnostic system is a significant step forward for surveillance programs that protect animal industries from emerging threats.

1.2. Scope and Limitation of the Study

Our research focuses on developing an automated system to identify LSD lesions in cattle. The primary goal is to use Inception v3 for feature extraction and Support Vector Machine (SVM) as the classifier for efficient lesion classification. The methodology begins with data collection, followed by preprocessing and augmentation. After this, Inception v3 extracts features, which are then classified using SVM. While the research follows a structured approach, we acknowledge several constraints that impact the study. The model training process requires a diverse and extensive dataset due to the varied nature of LSD lesions. This variety is necessary to ensure the model can predict accurately across different scenarios (Dommeti et al., 2023). The real-world application of this method could be influenced by image quality variations, inconsistent lesion features, and background interference. These factors must be considered in evaluating the limitations of the study, as they may affect the accuracy of the results.

1.3. Significance of the Study

This research has significant implications for livestock production, animal welfare, and sustainable farming practices (Fernandes et al., 2021). By integrating automation into the diagnostic process, the proposed system can transform the diagnosis and management of LSD. It enhances disease identification by improving diagnostic speed, precision, and reliability, which allows for the prompt detection of outbreaks, leading to quicker containment and reducing the economic impact of LSD. Furthermore, an automated, standardized diagnostic tool is essential for building sustainable practices within the livestock industry. This system provides stakeholders with a reliable method to detect and classify diseases, thereby enhancing the industry's capacity to address future challenges. The incorporation of automation into LSD diagnosis and management is a key advancement, improving disease control efforts across the livestock sector. The research also addresses current diagnostic challenges, laying the groundwork for improved animal healthcare practices. The ultimate goal is to strengthen the livestock sector, ensuring sustainable food production, animal welfare, and adherence to agricultural ethical standards.

1.4. Related Work

LSD has emerged as a major concern for livestock, especially in northern-hemisphere countries, caused by the LSDV, genus *Capripoxvirus* within the Family *Poxviridae*, it primarily affects cattle and water buffalo, with wild ruminants serving as virus carriers. The disease's increasing incidence is linked to environmental changes and spread through arthropod vectors (Han et al., 2023). The traditional diagnostic approach relies heavily on visual inspection, which can lead to inconsistencies due to subjective evaluations by different personnel (Duguma, 2016). This inconsistency highlights the need for objective, standardized diagnostic methods. LSD manifests through swollen skin nodules, which are a clear marker of the disease. The disease is widespread across Africa, Asia, and the Middle East, with significant economic and welfare implications for livestock populations (Roche et al., 2021). Existing diagnostic methods, such as manual inspection and blood sampling, have limitations. Laetitia et al. (2021) suggest that ear notches and skin biopsies can be more effective, improving both diagnosis and surveillance.

Machine learning (ML) is increasingly being applied in veterinary diagnostics. Previous studies have shown success using ML to detect other animal infections, such as foot-and-mouth disease and mastitis (Verma et al., 2021; Wang et al., 2022). Recent studies have applied ML to analyze the correlation between environmental factors and LSD outbreaks. For instance, Sanya et al. (2023) achieved 98% accuracy in predicting LSD occurrences using various ML algorithms. Similarly, Neha et al. (2022) found that the Random Forest algorithm achieved 97.7% accuracy in identifying LSD from dataset analysis. Furthermore, research by Safavi (2022) demonstrated the predictive capability of ML algorithms like artificial neural networks (ANN), which reached an AUC of 0.97 and an F1 score of 0.94 in forecasting LSDV occurrence. These results suggest that ML methods can enhance proactive disease monitoring and support vaccination programs.

Deep learning techniques, such as convolutional neural networks (CNNs) and Inception V3, have proven effective for image analysis, including feature extraction. These models automatically learn distinctive features from raw inputs, making them particularly useful for classifying LSD lesions in cattle (Ma et al., 2021; Jogin et al., 2018). Given the lack of scientific evidence on ML-based automation for LSD lesion classification in veterinary medicine, this study aims to fill the gap. By combining ML and deep learning approaches, the research seeks to develop an advanced artificial intelligence solution for accurate and efficient LSD lesion classification. This innovation could significantly improve livestock healthcare and disease management, enabling faster diagnoses and more effective treatment strategies for LSD-infected cattle.

2. Methods

The comprehensive overview in Fig. 1 outlines the systematic steps for the study. It covers data collection and preprocessing, feature extraction, SVM classifier implementation, model training, and evaluation procedures. These methods were carefully executed to meet the research objectives.

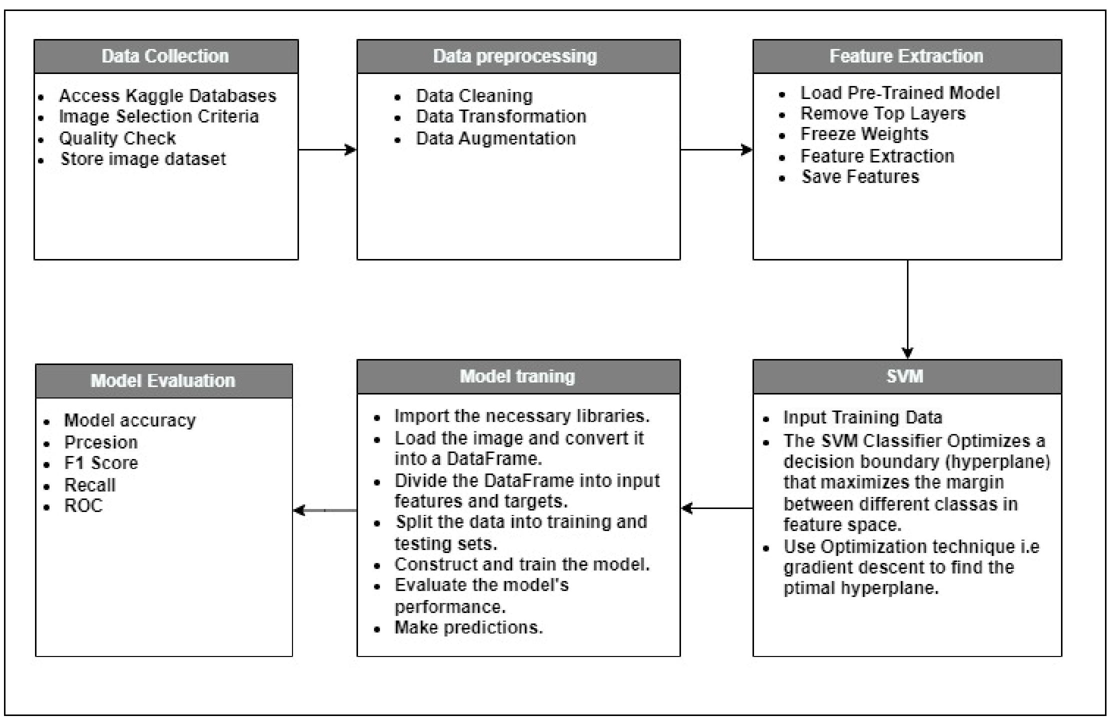

Fig. 1. Overview of the Proposed Methodology: Associating Automated Classification with Lumpy Skin Disease (LSD).

2.1. Data Collection

A dataset of three thousand images, featuring different types of cattle, was sourced from the Kaggle dataset (sample shown in Fig. 2). Kaggle is a well-known platform for data science and machine learning, providing access to various datasets, competitions, and educational resources (Banachewicz et al., 2022). The dataset contains two classes: images of healthy cattle and images showing cattle with LSD symptoms. A selection process for image data validation was performed after retrieving the files. This involved verifying file formats for compatibility, examining metadata annotations for image dimensions, and conducting resolution tests for clarity. Visual inspections were carried out to identify issues such as image corruption or duplicates, which could compromise data integrity. Validation measures were applied throughout the dataset to ensure consistency and accuracy, preventing analytical inconsistencies. The validated images were stored securely on a personal computer and organized for easy future use, with complete documentation for reference.

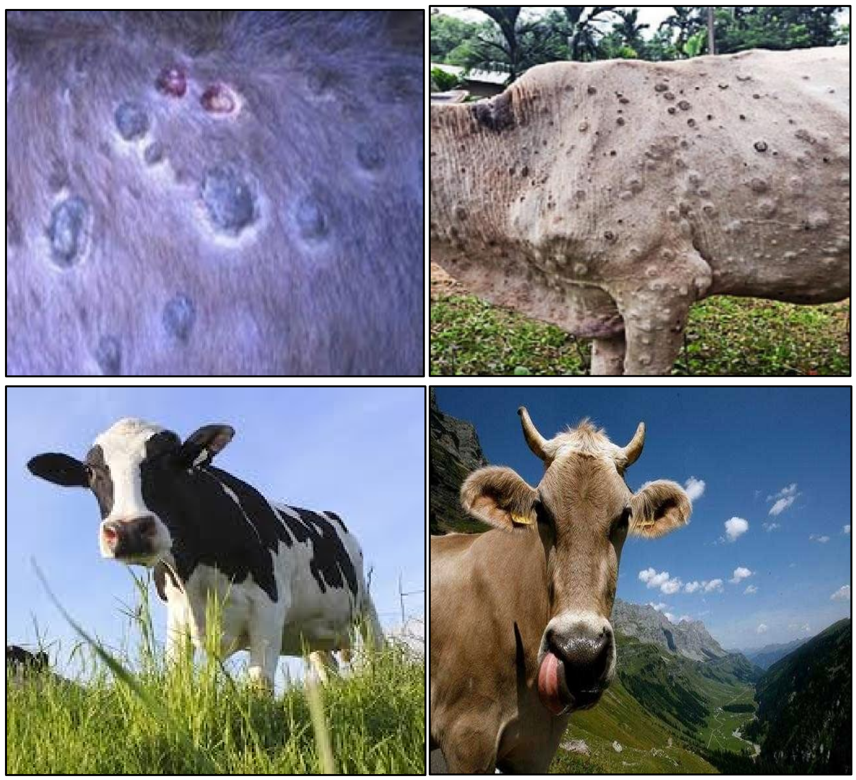

Fig. 2. Visuals of a sample from the dataset obtained from Kaggle.

2.2. Data Preprocessing

The dataset underwent essential pre-processing techniques to meet the conditions for model execution. All images were resized to 800×600 pixels to ensure uniformity before being fed into the machine learning model. Pixel values were normalized to the [0,1] range before training to enhance pattern recognition during the learning process. Augmentation techniques included rotation, scaling, flipping, and cropping (Alomar et al., 2023). The primary goal of augmentation was to improve model robustness by exposing it to variations within the dataset. This process helped the model develop better recognition capabilities, allowing it to handle new data more effectively. Augmentation also reduced the risk of overfitting by increasing data variability in the training set. The pre-processed dataset was divided into training and testing subsets for model evaluation. The training set, comprising 80% of the data, was used to teach the model to recognize patterns. The remaining 20% formed the testing set, which was exclusively used to assess the model's predictive accuracy on unseen data. This approach ensured a reliable evaluation process. The systematic organization of data and thorough pre-processing contributed to successful model development and enhanced reliability in machine learning applications.

2.3. Feature Extraction

The study employs Inception V3 as a feature extraction algorithm to transform cattle lesion images into discriminative features. Inception V3 captures the complex visual structure of lumpy skin disease (LSD) lesions, enabling precise analysis. Its combination of versatility, efficiency, and high performance makes it a suitable model for feature extraction in this research. Inception V3 is a Convolutional Neural Network (CNN) architecture known for its exceptional performance in image classification, object detection, and feature extraction (Mathina et al., 2023). Developed by Google, it improves upon the original Inception model with optimized accuracy and processing speed. The model's inception modules consist of multiple convolutional layers with filters of varying sizes, allowing it to analyze features across multiple spatial scales. These modules help extract both fundamental and complex image patterns. Factorized convolutions and dimensionality reduction techniques reduce computational costs while maintaining high performance. The feature extraction architecture of Inception V3 is outlined in Fig. 3.

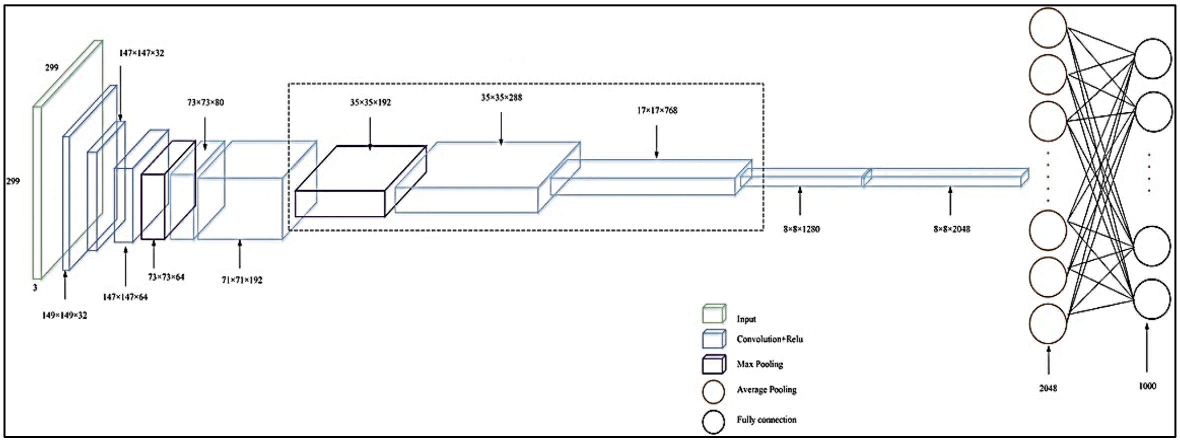

Fig. 3. Feature extraction using the Inception V3 model includes harnessing its deep convolutional layers to extract meaningful features from input images. The process leverages the architecture's inception modules, which capture features at various scales and complexities within images (Cao et al., 2021).

Inception V3 incorporates a Batch Normalization (BN) layer between the auxiliary classifier and the fully connected (FC) layer to serve as a regularizer. The BN model utilizes the batch gradient descent method to accelerate deep neural network training and improve model convergence. The Batch Normalization (BN) equations are as follows:

$$B = \{x_{1\ldots m}\}, \gamma, \beta \qquad (1)$$

$$\{Y_i = BN_{\gamma,\beta}(x_i)\} \qquad (2)$$

$$\mu_B \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad (3)$$

where x is the minimum activation value of batch B, m is the number of activation values, and γ and β are learnable parameters. γ adjusts the variance in the value distribution, while β controls the position of the average value.

2.4. Machine Learning Model

Support Vector Machines (SVMs) were used as the classifier in this study. Since the problem required a binary classifier, SVMs were an appropriate choice. The SVM-based classification system was developed using a structured pipeline. The classifier utilized feature vectors extracted from images, following the process outlined in the Feature Extraction section (Liu et al., 2020). A linear kernel function was selected as the best fit for the dataset. In SVM, a linear kernel represents the dot product between feature vectors. It measures the similarity between two data points and helps determine the optimal hyperplane for separating them into distinct classes, as shown in Equation 4.

$$K(\mathrm{x}, \mathrm{y}) = \mathrm{x} \cdot \mathrm{y} = \sum_{i=1}^{n} x_i y_i \qquad (4)$$

where n is the number of features in the vectors x and y, and x_i and y_i are the corresponding feature values.

2.5. Model Training

The training process allows the algorithm to recognize different cattle types by defining optimal decision boundaries based on image attributes. The first step involves preprocessing labelled training images to extract discriminative features. The SVM algorithm then undergoes an iterative optimization process to maximize the margin between support vectors near the decision boundary. This optimization enhances the model's generalization ability on new datasets by minimizing classification errors. During training, SVM solves a constrained optimization problem to identify the optimal separating hyperplane for maximum margin classification. Kernel-based techniques enable the model to handle nonlinear relationships by mapping input data to higher-dimensional spaces. In the testing phase, the trained SVM model classifies new images accurately by applying learned data patterns.

2.5.1. Parameters used for inception v3

a) Input Image Size: 224 × 224 × 3
b) Feature Extraction Layer: Global Average Pooling (GAP)
c) Activation Function: ReLU
d) Optimizer: Adam
e) Learning Rate: 0.0001
f) Batch Size: 32
g) Epochs: 30

2.5.2. Algorithm of the Proposed Method

I. Set the bias and weights to zero at the beginning.
II. Define the parameters (i.e. iterations, learning rate etc.).
III. For each iteration:
   a. Determine the dot product of the input data and the weights.
   b. Use the sigmoid function to calculate the expected result.
   c. Determine the error.
   d. Use the error and learning rate to update the weights and bias.
IV. Give the bias and weights back.

3. Model Evaluation

The evaluation phase requires multiple metrics and methods to assess model performance and its ability to predict unseen data. Key evaluation elements include dataset partitioning into training, validation, and testing sets. Metrics such as accuracy, precision, recall, F1-score, and cross-validation are used. Confusion matrices and learning curves help track model performance. Thorough evaluation ensures the selection of the best model, parameter optimization, and identification of improvements.

4. Results and Discussion

4.1. Visual Outputs

This section presents the results of the SVM-based classification for cattle with LSD lesions. The model's accuracy is demonstrated in Figures 4 and 5, where it correctly identifies and distinguishes the key features of LSD in cattle. The visual representations provide clear evidence of how the SVM classifier utilizes visual attributes to separate unhealthy cattle from healthy ones. The model effectively excludes healthy cattle from the dataset (Figure 4). These results confirm the SVM classifier's ability to accurately identify both diseased and healthy cattle, supporting its use in precise disease diagnosis and management.

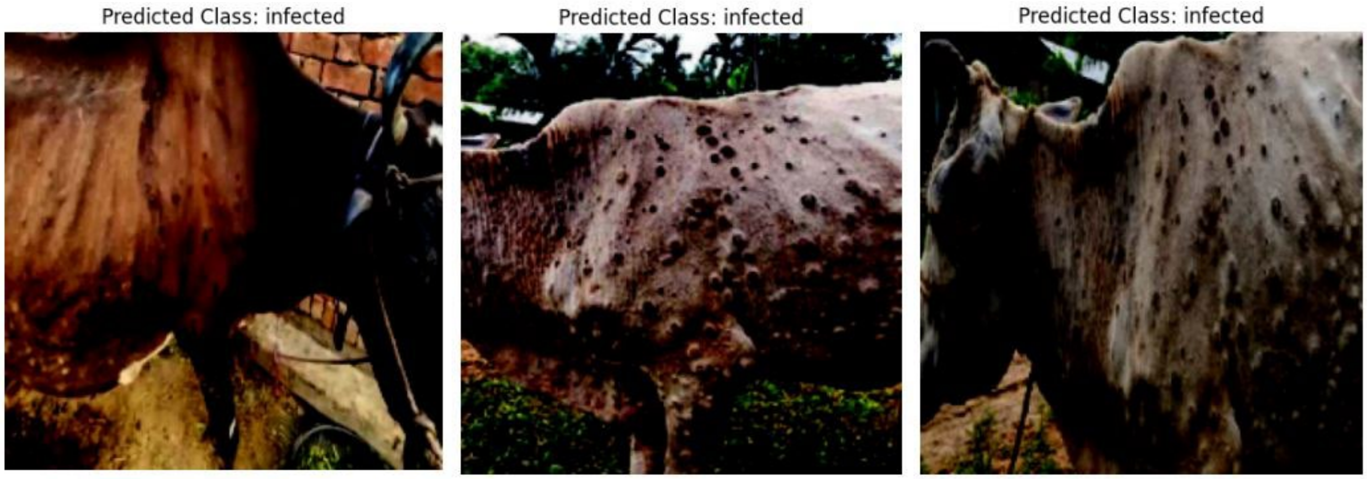

Fig. 4. The efficiency of the proposed approach in accurately identifying and classifying cattle with LSD, highlighting its potential for disease diagnosis.

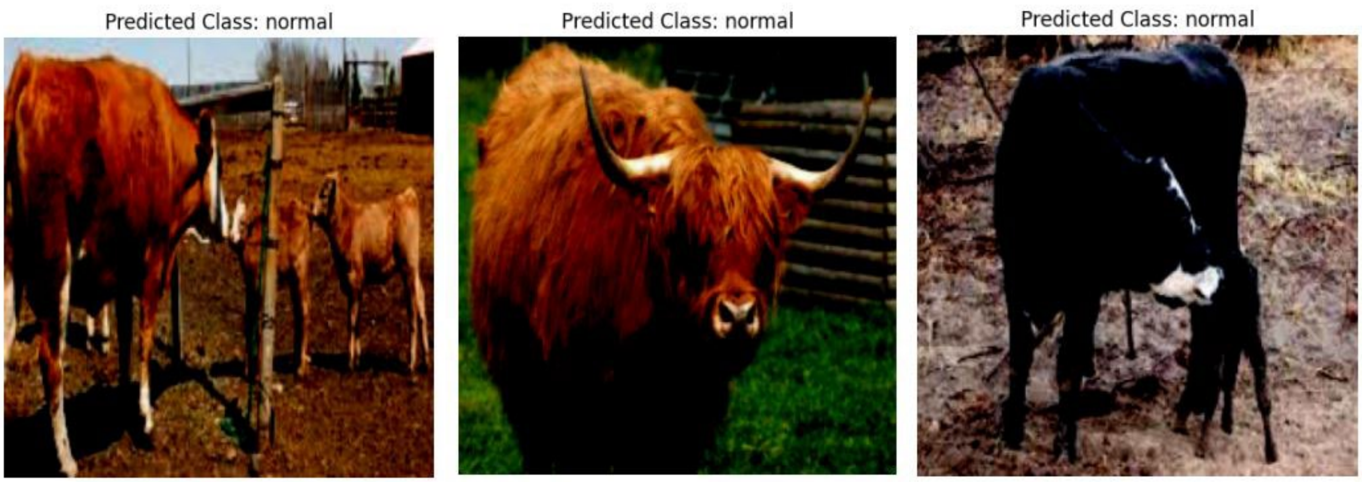

Fig. 5. The precision of our model in accurately classifying healthy cattle, emphasizing the robustness of our machine-learning approach for LSDV detection and management.

4.2. Discussion

The proposed model demonstrates promising performance metrics, as shown in Table 1, highlighting the effectiveness of automated approaches in identifying and classifying LSD lesions in cattle. The model achieved 80% precision in differentiating healthy skin from LSD-infected skin, proving its ability to distinguish diseased from healthy animals. It also displayed strong precision, minimizing errors in classifying healthy animals during LSD detection. With an 82% F1-score, the model shows balanced performance by focusing on retrieving valid positive outcomes while reducing false negatives across different infection stages. The model's performance remained consistent, accurately classifying cattle regardless of LSD lesion severity. It achieved 84% accuracy in interpreting lesion severity and 83% recall in detecting diseased cattle at various infection points. This model proves capable of accurately categorizing LSD lesions, aiding proper treatment planning and management decisions. It demonstrates the potential of automated classification methods to improve veterinary disease management in the livestock sector. The adoption of such automated systems could strengthen disease monitoring, speed up disease recognition, and allow immediate response actions. However, limitations exist, such as the need for robust datasets for generalization and consideration of external factors like image quality and lesion variability. Further research is necessary to refine these models and explore innovative machine learning approaches for enhanced disease management. Addressing current challenges will make efficient disease management in the livestock industry possible through advanced automated classification methods. Moreover, Figure 6 shows the visual representation of the results as shown in Table 1.

Table 1 The evaluation metrics, including accuracy, precision, recall, and F1 score, provide insights into the performance of our model.

S. No	Metric	Value
1	Accuracy	0.84
2	Precision	0.80
3	Recall	0.83
4	F1 Score	0.82

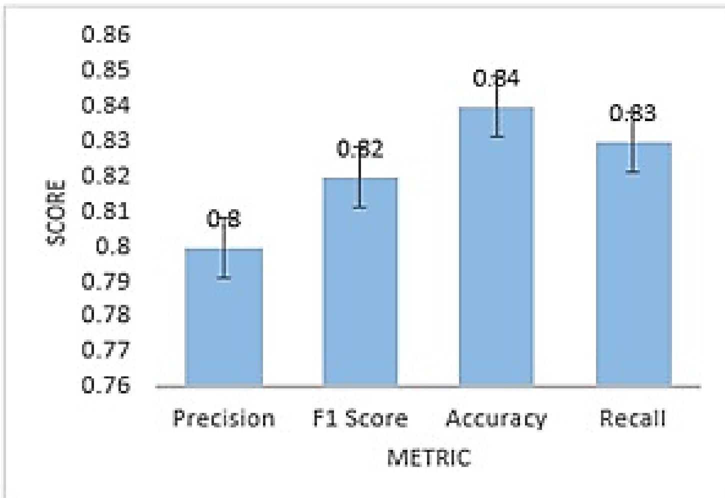

Fig.6. A graphical representation of the evaluation metrics, including accuracy, precision, recall, and F1 score, offers a visual depiction of the model's performance.

4.3. Confusion Matrix

To assess an in-depth understanding of the classification model's performance, a confusion matrix for each severity class is presented. As shown in Figure 7, the matrix clarifies misclassifications and illustrates how accurately the system identifies disease occurrences.

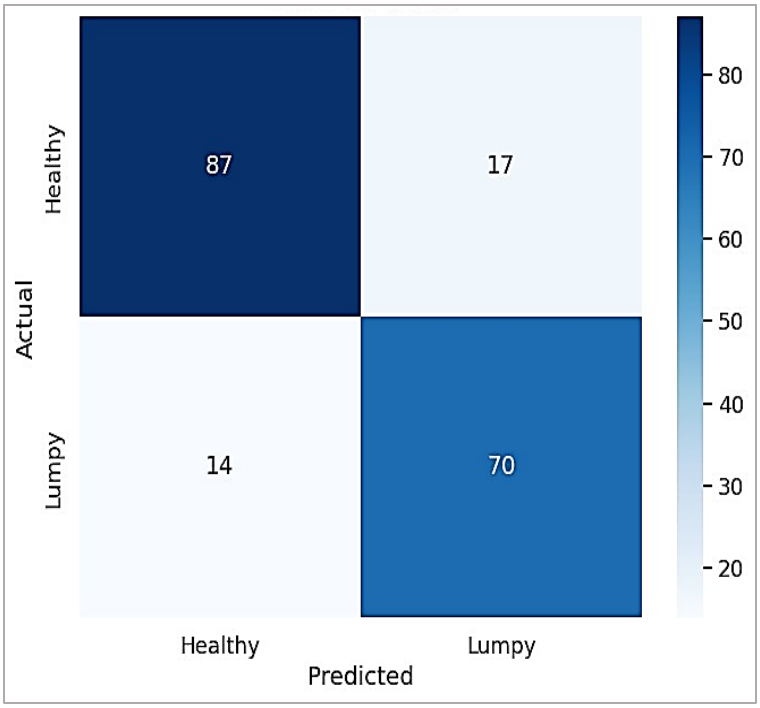

Fig. 7. The Confusion matrix visually presents the actual versus predicted classifications predicted by the model. It provides a comprehensive view of the model's performance by revealing the number of true positive, true negative, false positive, and false negative predictions.

4.4. ROC Curve

The model's predictions yielded an ROC curve by plotting TPR and FPR values while varying the threshold settings. TPR represents the proportion of correctly classified positive cases, while FPR reflects the proportion of false positives identified by the model. The model's discrimination ability was evaluated using AUC, which generates a numerical value from the ROC curve. The obtained AUC value in Figure 7 is 0.89, demonstrating strong performance, as a perfect classifier would achieve an AUC of 1.

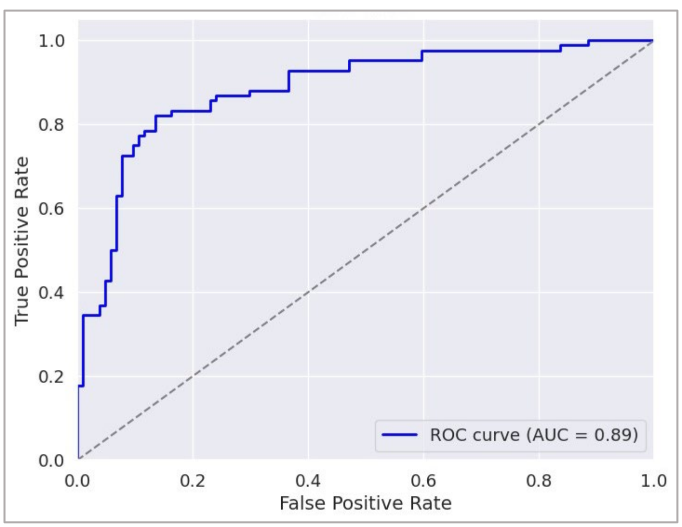

Fig. 8. Graphical representation of the Receiver Operating Characteristic (ROC) curve derived from the trained model's performance.

4.5. Learning Curve

Learning curves reveal insights into the model's generalization and the presence of overfitting or underfitting by graphing the model's performance metrics against varying amounts of training data. The results shown in Figure 9 indicate that the model performs well on both training and validation sets as the training dataset size increases, with validation performance converging to a stable value. The data in Figure 9 demonstrates the model's optimal performance on both training and validation data, with the validation set stabilizing as the volume of training data grows.

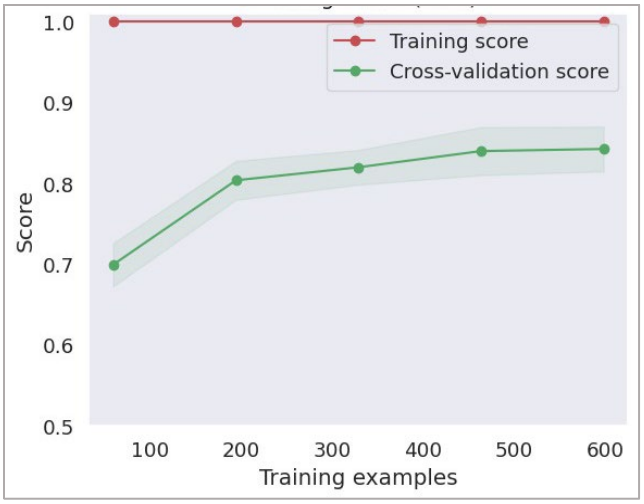

Fig. 9 Graphical representation illustrating the model's performance throughout the training and validation phases.

4.6. Comparative analysis of SVM with other models

The investigation compared four machine learning algorithms—Support Vector Machine (SVM), Logistic Regression, Random Forest, Decision Tree, and AdaBoost—using four performance metrics. The results, shown in Table 2, indicate that these algorithms performed optimally in classifying Lumpy Skin Disease (LSD) lesions.

- Logistic Regression: Accuracy = 0.79, Precision = 0.75, Recall = 0.48, F1 Score = 0.61.
- Decision Tree: Accuracy = 0.80, Precision = 0.67, Recall = 0.64, F1 Score = 0.63.
- Random Forest: Accuracy = 0.83, Precision = 0.81, Recall = 0.71, F1 Score = 0.79.
- AdaBoost: Accuracy = 0.77, Precision = 0.67, Recall = 0.72, F1 Score = 0.30.
- Support Vector Machine (SVM): Accuracy = 0.84, Precision = 0.80, Recall = 0.82, F1 Score = 0.83.

SVM yielded the highest performance as a tool for identifying LSD lesions in cattle, with superior accuracy, precision, recall, and F1 score.

Table 2. A comparative analysis of the Support Vector Machine (SVM) and other algorithms used for classifying Lumpy Skin Disease (LSD). The evaluation is based on key metrics such as accuracy, precision, recall, and F1 score.

Algorithm	Accuracy	Precision	Recall	F1 Score
Logistic Regression	0.79	0.75	0.48	0.61
Decision Tree	0.8	0.67	0.64	0.63
Random Forest	0.83	0.81	0.71	0.79
Adaboost	0.77	0.67	0.72	0.3
Proposed model (SVM)	**0.84**	**0.80**	**0.82**	**0.83**

The results of Table 2 is visualized in fig 10. Which can display a clearer view of the data to understand.

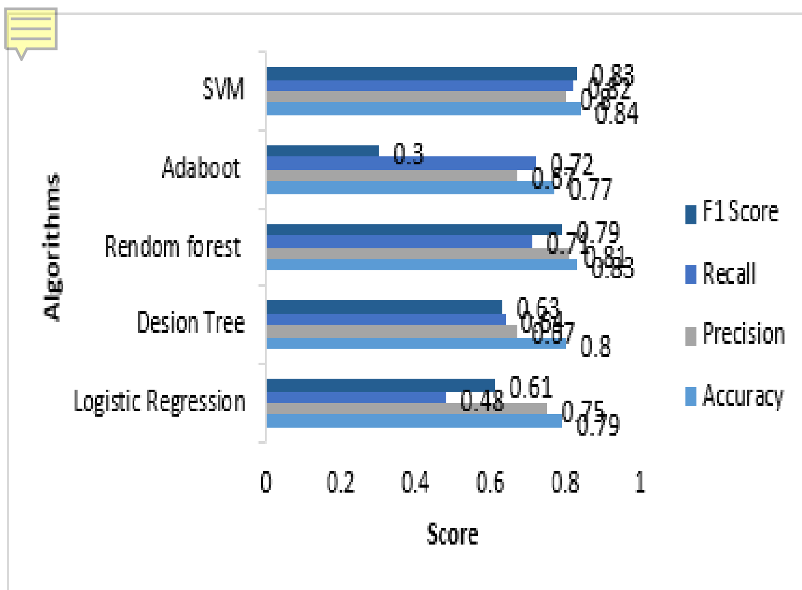

Fig. 10. A comparative bar chart visualizing the performance of the Support Vector Machine (SVM) alongside other algorithms used for classifying LSD

4. Conclusion

The SVM-based classification method in this research presents an effective automated system for identifying and categorizing LSD in cattle. The model demonstrates exceptional performance, with high precision, accuracy, recall, and F1 score, effectively detecting and classifying LSD lesions. These findings offer valuable insights for improving disease management practices. However, the study acknowledges limitations, including potential dataset biases, and highlights opportunities for enhancing the system. Future research should address these limitations and explore new methods to improve performance for real-world applications. The results contribute to advancing automated disease detection in livestock and offer new possibilities for LSD surveillance and management.

Declarations

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflicts of interest or funding issues arose during the preparation of this meta-analysis manuscript.

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Author contributions: Asad Ullah conceptualized the idea. Fakhre Alam wrote the main manuscript text, and Naveed Khan, Mohammed Rohaim and Muhammad Munir interpreted the data and reviewed the manuscript.

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Data availability: The authors have stated that the data supporting the results of this study can be accessed within the article upon reasonable request.

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