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Detecting high-risk Area for Lumpy Skin Disease in Cattle Using Deep Learning Feature

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Abstract

Cattle's lumpy skin disease is a viral disease that transmits by blood-feeding insects like mosquitoes. The disease mostly affects animals that have not previously been exposed to the virus. Cattle lumpy skin disease impacts milk, beef, and national and international livestock trade. Traditional lumpy skin disease diagnosis is very difficult due to, the lack of materials, experts, and time-consuming. Due to this, it is crucial to use deep learning algorithms with the ability to classify the disease with high accuracy performance results. Therefore, Deep learning-based segmentation and classification are proposed for disease segmentation and classification by using deep features. For this, 10 layers of Convolutional Neural Networks have been chosen. The developed framework is initially trained on a collected Cattle's lumpy Skin Disease (CLSD) dataset. The features are extracted from input images; hence the color of the skin is very important to identify the affected area during disease representation we used a color histogram. This segmented area of affected skin color is used for feature extraction by a deep pre-trained CNN. Then the generated result is converted into a binary using a threshold. The Extreme learning machine (ELM) classifier is used for classification. The classification performance of the proposed methodology achieved an accuracy of 0.9012% on CLSD To prove the effectiveness of the proposed methods, we present a comparison with the state-of-the-art techniques.

Keywords: *Classification, deep learning, lumpy skin disease, optimization, segmentation*

1. Introduction

Cattle's lumpy skin disease is a viral disease that transmits by blood-feeding insects like mosquitoes [1]. The livestock sector globally is highly dynamic, contributes 40 % of the global value of agricultural output, and supports the livelihoods and food security of almost a billion people [2]. Keeping the safety of livestock sectors is safe as securing the life of those millions of dependents on livestock at specific and caring for the world at large.

Figure 1. Lumpy skin disease

The lumpy skin disease is a more virulent cow disease that affects most cattle. The disease is contagious, and it has the potential to spread across borders, affecting neighboring countries. Due to lower output and restrictions on the international trade of live animals and animal products, the disease causes enormous economic losses. As a result, the disease's transmission and spread are tied to warm and humid climatic conditions associated with high biting arthropod population densities [2, 3].

Most cattle owners (farmers) follow a set of stages for lumpy skin disease treatment, beginning with traditional medicine (like watering some natural leaf, burning the area where they found the problem), and finally taking to Veterinary Doctor. This is time-consuming, and the diseases are diagnosed far too soon. Other

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issues, particularly in underdeveloped countries in Sub-Saharan Africa, include the inability to find a veterinarian.

Professional doctors are hard to come by, especially in the Continent of Africa. As a result, machine learning approaches play a crucial role in lumpy skin disease early treatment. Machine learning offers an alternative to challenges, is quicker, and is far more accurate in both combating and detecting disease. In contrast, machine Learning approaches are superior to manual detection and treatment. Convolutional neural networks (CNNs) with multiple convolutional layers are typically used in deep learning feature extraction [4,5].

In the first phase, a deep CNN method is used to locate the area of an infected location. In the second phase, the extracted feature must then be classified into the appropriate category, such as lumpy skin disease or non-lumpy skin disease. There are several difficulties during the classification process because of the following factors: (i) there isn't much of a color difference between various skin diseases and lumpy skin-affected regions, and they can even be mixed; in this scenario, confusion and incorrect conclusions may result. (ii) detection is challenging due to camera resolution quality. (iii) there is no database prepared for this purpose to the best of my knowledge. Therefore, it will be difficult to compare the state of the art. However, we use alternative solutions to overcome these issues.

According to the findings of the study, selecting the best features and using the results in feature fusion yields promising results [6-8]. As a result, we used multiple Fusion approaches to increase the number of features gathered from a Region of Interest (ROI) that is accessible from a variety of locations. Even though this phase increases the number of predictors, which increases computational time, we chose the best features using a meta-heuristic approach feature selection strategy. Based on the selection process, meta-heuristic procedures are more useful and have a reduced number of predictors [9]. In section two of this works several fusion and selection approaches have been discussed.

We employ the cattle's lumpy skin disease in this study, which is divided into two categories: lumpy skin disease and non-lumpy skin disease. Because the images in this dataset are not evenly distributed, training a CNN model with it is extremely difficult. Ear, back, pin, tail, thigh, toe, stomach, elbow, chest, brisket, neck, and many features such as hand, face, neck, foot, and so on are all included in this dataset. Each class has a varied number of images in it.

The key challenges in using these datasets include low contrast in the affected area, high irregularity, and lumpy in the joint area. This article introduces a mechanism for segmenting and classifying lumpy skin disease images into lumpy skin disease and non-lumpy skin disease. The foremost contributions are mentioned as under:

i. A dataset of different Cattel's Lumpy Skin Disease (CLSD)is prepared.
ii. For skin image enhancement we presented local color-controlled histogram intensity values (LCcHIV), to boost the local contrast of a lumpy region.
iii. We offer a novel 10-layer CNN-based deep learning-based technique for segmenting lumpy regions.
iv. Finally, we applied the Extreme Learning Machine for classification.

The rest of the manuscript is organized as follows: The introductory section and the literature review section are included in Sections 1 and 2, respectively. Materials and methods are presented in Section 3, with a detailed mathematical explanation and visual results. Section 4 discusses the experimental setup and results. Finally, the conclusions are given in Section 5.

2. Literature Review

A lot of work has been done in the lumpy skin disease and human cancer detection and segmentation area but, to the best of my knowledge, there are not too many technical studies exist in the computer vision field for cattle's lumps skin disease. I only found theoretical work related to this study. The theoretical works I found have been presented on qualitative assessment transmission of lumpy skin disease [9]. To find the transmission possibility of the disease they used probability to assess the risk. Lately, several computer vision and machine learning-based methods are introduced for the segmentation and classification of diseases in human health. An automated approach for lung cancer classification based on classical and transfer learning from a chest radiograph [10]. The introduced system consists of two major stages segmentation and classification. An approach for feature selection is adopted which chooses the optimum features for final recognition. The system achieved higher than 90% accuracy for all considered disease types. Human skin cancer is also discussed in some literature some of which are discussed in this section. In this work, they tried to classify dark spots/bubbles around found in the human body [11]. The high pass filter is used to highlight the edges; further, illumination is removed by a homomorphic filter [12]. Segmentation is a crucial step and provides significant information about cancer such as border, shape, asymmetry, and irregularity [13]. Morphological filtering with weight-based features selection approach is used for the detection of lesion boundaries [14]. After features extraction, classification is done to discriminate the affected region into benign/malignant. The KNN, decision tree [15], and SVM [16] are used for classification. Deep learning methods [17-19] are mostly utilized for cancer detection [20]. Esteva et al developed GoogLeNet and Inception V3 CNN models for skin cancer classification. AlexNet [21, 25] model is applied to the dataset to learn the pattern of cancer. The extracted features pattern in the form of the vector is passed to the multiclass SVM for discrimination among the healthy and infected regions. A deep full resolution convolution network (DFRCN) with a SoftMax layer [27] is used for classification.

3. Materials and Methods

This section discusses materials and implementation used for cattle lumpy skin disease.

3.1. Proposed Methodology

Our proposed method consists of four major steps that are: (i) Stretching of disease-infected area (ROI), in this step we perform the segmentation of the infected region. We apply feature extraction from segmented regions once the affected region has been identified. The existence of too many infected regions is the main obstacle to accurate segmentation of the infected area. As a result, contrast stretching is crucial for quality improvement since it eliminates the effects of noise.

Extraction of important features for accurate classification is the second significant problem. As a result, in this research, we focus primarily on the following factor that impacts the outcomes: a) low contrast between infected and healthy regions; b) similarity of texture patterns between infected and healthy regions; c) dissimilarity of images caused by lighting and illuminating effects; d) use of unrelated features; and compatibility of chosen classifiers. In terms of accuracy, sensitivity, precision, and computational time, this will help us enhance disease detection and recognition effectively. (ii) Deep feature extraction, Efficiency of automation is overly dependent on feature sets. While weak and redundant features degrade system performance, strong and distinctive, features may improve the model performance. The so-called ABCD rule [22, 24, 28, 29] is the framework for feature extraction in our work. The ABCD represents the lumpy's asymmetry, border structure, color variation, and skin structure, and defines the basis for a diagnosis Veterinarian.

We employ two different kinds of features at this stage: global features and local features. The entire structure is represented by a single feature vector for the global feature. We examine a lumpy's size, symmetry, and color descriptors in global features. During the training phase of the local feature, images are sampled into small patches, and each patch is given a feature vector to represent it. We can characterize the many regions of the lumpy more precisely by breaking it up into smaller pieces. In a patch, less than 50% of the lumpy pixels are eliminated. (iii) feature fusion, in this step, several feature vectors are retrieved and combined into one feature vector. Then, the classification model is fed the obtained result. (iv) classification. Finally, we applied Extreme Learning Machine (ELM) to classify features. The detailed proposed flow is shown in **Figure 2**.

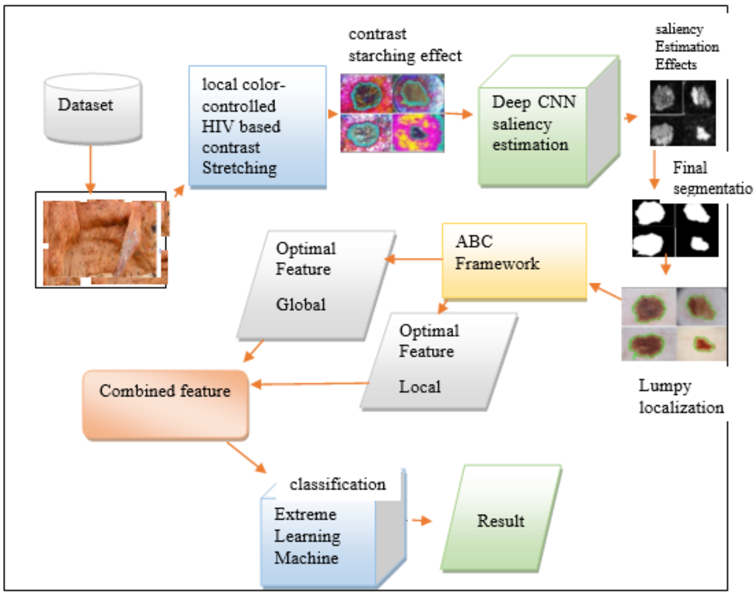

Figure 2. *Proposed systematic diagram of lumpy skin disease classification.*

3.2. Dataset

The proposed framework is validated using the CLSD dataset. There are 1100 image samples in this dataset.

Of these 800 images are for training, 200 images are for testing, and 100 images are for validation. Lumpy skin disease and non-lumpy skin disease classes are included in the training examples.

Figure 3. *(a) and(b) Lumpy affects various parts of the body.*

To enhance the size of the dataset, all the cattle bodies that can be affected by the disease are included. **Figures 3**, a, and b show some samples from the dataset, representing different body sections that can be afflicted by lumpy diseases, such as the ear, back, pin, tail, thigh, toe, stomach, elbow, chest, brisket, and neck. **Table 1** shows the lumpy affected body samples used in training.

Table 1. *Lumpy skin disease dataset detail*

Class	Ear	Back	pin	Tail	Tight	Toe	Stomach	elbow	chest	Brisket	Neck
Sample	60	54	60	60	55	50	60	50	41	50	60

During the training of the model on the datasets, there are three primary steps: lumpy detection, lumpy segmentation, and lumpy classification. Image quality is critical for detecting lumpy affected regions. Intensity enhancement is the most effective approach to improving image quality. Improving the quality of an image by enhancing a few features or lowering the amount of blockage between various image pixels. The main goal of this stage is to boost the contrast of the affected area so that the lumpy skin disease-affected region of interest (ROI) can be done easily. We build a histogram equalization (HE) and refine the findings to detect the bumpy pixels in the input image. The intensity values are then increased and changed according to the lumpy and background regions using a fitness function. A brief description of the procedure is as follows: The input image x, y, which has N x M dimension and where (x, y) εR. The histogram of the image is computed using equation 1.

$$h_f(k) = Oj \tag{1}$$

where hf(k) is the histogram of an image, f represents the frequency of occurrences, Oj represents the occurrence of gray levels, and j Ɛ = 0, 1, 2, . . . K - 1. Based on hf(k), we find

$$\sim h_f(k) = \quad h_f(k)[I_j]k1,\ kn, \tag{2}$$

the range of infected pixel, where I represent the infected region and j represents the pixel values. The ~hf (k) is the entire infected region, and the range of the infected region is represented by k1 to kn. Equation 3 is used to calculate the overall image Varian minuses

$$\sigma(\xi xy) = \frac{1}{MN}\sum_{i=0,j=0}^{N-1,M-1}(\xi ij)2 - \mu^2 \tag{3}$$

$$\mu = \sum_{i=0,j=0}^{M-1,N-1}(\xi ij) \ * \ \frac{1}{MN} \tag{4}$$

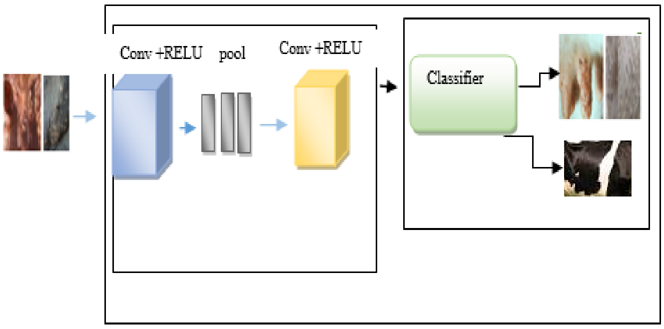

Figure 4. *Proposed model for lumpy skin disease*

The convolutional layer weight matrix and bias matrix are represented as follows

$$C = \sum \xi xy + w + b \tag{5}$$

where C denotes features of the first convolutional layer, x, y is an enhanced image, W is the weight matrix of the lth layer, and b is the bias matrix of the lth layer. After that, the ReLu activation layer was applied. In the second convolutional layer, the filter size was [3, 3], the number of channels was 64, the number of filters was 64, and the stride was [1, 1]. The features of this layer were normalized using the ReLu activation function. Next, a max-pooling layer was applied of filter size [2, 2] and stride of [2, 2]. The main purpose of this layer was to obtain more active features and minimize the feature-length. Equation 2 (see above) is multiplied by the output variance value obtained from this formula. Thereafter, we combine the results. In addition, the infected patch is subjected to histogram equalization before being fused with the original image.

Before being fused with the original image, the infected patch is also subjected to histogram equalization. Later, the image is loaded into (i) a ten-layer CNN model; (ii) features of the final convolutional layer are visualized and concatenated in one image; (iii) super pixels of the concatenated image are computed; (iv) a threshold is applied for final segmentation; and (v) boundaries are drawn on segmented regions using an active contour approach for the localization of lumpy affected areas.

We used these images to create a simple CNN model using output enhanced images with the size of 512 x 512 x3. This approach is mostly used to learn and visualize picture attributes. **Figure 4** depicts the designed model visually. One input layer, three convolutional layers, including the ReLu layer, one max-pool layer, one fully connected layer (FC), one SoftMax layer, and finally an output layer make up this model. We scaled all photos to 224 x 224 x3 because the input layer's size was 224 x 224 x 3. The filter size was [3, 3], the number of channels was 3, the filter size was 64, and the stride was [1, 1] in the first convolutional layer. We got two feature matrices after this layer: the weight matrix and the bias matrix. The weight matrix was 3 x 3 x 3 x 64 bytes in size, and the bias matrix was 1 x 1 x 64 bytes in size.

4. Experiment result

In this section, we discuss the steps and parameters that were employed during the computation of results. In the lumpy segmentation process, we tested the proposed model. During testing, the proposed model accuracy and error rate were both considered while segmenting lumpy. Multiple classifiers were employed in the classification process to compare the Extreme Learning Machine (ELM)'s effectiveness. Naive Baye, Multiclass Support Vector Machine and Fine K-Nearest Neighbor were among the classifiers used to validate the selected classifier.

We employed various classifiers (Naive Bayes, SVM, FKNN) to validate the performance of our model throughout the validation phase. In Naive Bayes, the classifier employs the Gaussian function. Later, we used a Multi-class Support Vector Machine, which combined the kernel function with one versus the rest. Nearest Neighbor was utilized in Fine KKN. In FKNN we computed Euclidean distance. We sated k to 10, and the learning rate to 0.001. we used mini-batch gradient descent where a mini-batch size is set to 28. The tensor flow was used as a simulation tool. The proposed segmentation result has an overall accuracy of 95.38 percent. The findings were obtained utilizing the proposed framework, and the values obtained are listed in **Tables 2** and 3. Here, the lumpy segmentation numerical results are presented in **Figure 5**.

Table 2. Classifier Performance Measures

Classifier (%)	Naïve Bayes	SVM	ELM	Fine KNN
Accuracy (%)	0.7624	0.7750	0.906	0.7494

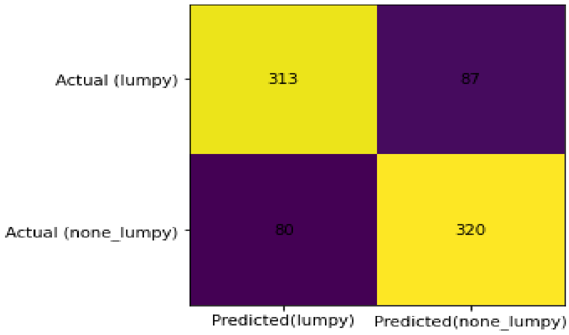

Figure 5. *Confusion matrix of the classifier model on lumpy skin disease dataset*

Table 3. *Confusion matrix of ELM classifier on cattle lumpy skin dataset*

Ear	0.90	0.00	0.01	0.02	0.01	0.01	0.02	0.01	0.02	0.01	0.02
Back	0.00	0.91	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.01	0.01
Pin	0.01	0.01	0.90	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Tail	0.00	0.00	0.01	0.91	0.00	0.01	0.02	0.01	0.02	0.01	0.02
Thigh	0.00	0.00	0.02	0.01	0.90	0.00	0.01	0.00	0.01	0.00	0.01
Teo	0.01	0.00	0.00	0.00	0.01	0.91	0.00	0.01	0.00	0.01	0.00
Stomach	0.01	0.02	0.00	0.02	0.02	0.01	0.91	0.01	0.02	0.01	0.02
Elbow	0.01	0.01	0.00	0.01	0.01	0.01	0.02	0.90	0.01	0.00	0.01
Chest	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.89	0.01	0.00
Brisket	0.01	0.02	0.00	0.02	0.02	0.01	0.00	0.01	0.02	0.90	0.02
Neck	0.00	0.01	0.00	0.01	0.01	0.00	0.02	0.00	0.01	0.01	0.89
	Ear	Back	Pin	Tail	Thigh	Teo	Stomach	Elbow	Chest	Brisket	Neck

4.1. State-of-the-art Comparison

We also tested our dataset to compare our results to the current state of the art. The outcome is shown in below. **Table 4** describes the classification performance of ResNet101 deep features. The ResNet101 deep features were extracted. The result shows the best accuracy of 80.46%. MSVM gave the second-best accuracy of 77.50%; however, it is noted that only the prediction time for ResNet101 features increased. Similarly, the classification performance while using only DenseNet201 CNN deep features is given in **Table 5**. The best accuracy in this experiment was 79.34%, while the worst accuracy was 74.30%.

Table 4. *Lumpy skin classification results using only the Faster- RCNN model.*

Classifier	Accuracy (%)	FNR (%)	Prediction Time(s)
NaïveBayes	82.36	26.36	161.2031
ELM	89.42	23.76	139.9897
KELM	85.34	19.54	142.0120
XGBoost	89.00	19.50	143.00
MSVM	87.50	22.5	138.9210
Fine KNN	78.94	25.06	146.7980

Table 5. *Lumpy skin classification results using the DenseNet201 CNN model.*

Classifier	Accuracy (%)	FNR (%)	Prediction Time(s)
NaïveBayes	75.64	24.36	172.6420
ELM	89.24	19.68	140.9260
KELM	88.46	21.82	142.3364

MSVM	88.16	19.78	141.2064
XGBoost	89.00	19.50	141.00
Fine KNN	78.30	24.01	135.3092

In **Table 6** the ELM and SoftMax classifiers were evaluated. Based on the results, the ELM algorithm increases the classification accuracy. The best accuracy achieved in this experiment was 83.04% on the ELM classifier, whereas the worst accuracy was achieved by a Fine KNN of 76.04%. Additionally, the prediction time was minimized after this experiment due to the reduction in irrelevant features. The best time of this experiment was 96.3248 (s) on MSVM, whereas the ELM was executed in 103(s).

Table 6. *Comparison of the proposed model.*

optimization Technique	Accuracy (%)	Sensitivity (%)	Error (%)
ELM	90.50	89.98	9.5
Softmax	87.45	87.52	12.55

The classification results of the proposed system are presented in **Table 7**. A 50:50 strategy is utilized for recognition purposes. The ELM shows superior performance as compared to other classification methods and achieved an accuracy of 94.1%. The few other measures include sensitivity, specificity, precision, AUC, and FP rate 94.50%, 94.70%, 94.68%, 0.998, and 0.0020, respectively.

For this work, Extreme Gradient Boosting (XGBoost) was used due to its tendency to yield incredibly accurate findings. As a result, XGBoost is preferred over other traditional classifiers for enhancing classification quality. As can be seen in **Table 7**, where XGBoost scored the highest result, it is one of the most effective approaches for classifying and showed promising results over the dataset.

Table 7. *Proposed classification*

Method	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
C-SVM	88.89	89.98	989.51	89.08
C-KNN	87.80	88.00	88.10	87.82
Q-SVM	89.01	89.20	89.00	89.03
ESD	89.00	89.89	90.00	89.80
M-SVM	89.00	89.00	90	89.11
XGBoost	90.01	89.00	89.25	89.92
ELM	90.01	90.05	90.19	90.06

5. Conclusion

This article proposed a model for cattle's lumpy skin disease segmentation and classification. In the framework, a deep learning-based segmentation method and CNN feature optimization were described. The proposed method was evaluated on the well-known datasets for cattle's lumpy skin disease. The result shows the model performance is promising. The best classification result considered in this work is the ELM classifier having an accuracy of 0.9012. The ELM is found to be the overall best, having better performance on the dataset. Yet, one of our work's constraints is computational time, which will be investigated in the upcoming work. Additionally, in future studies, we will enhance our segmentation technique to prevent training our deep models on irrelevant visual features.

Declaration of interest

The authors declare that there is no conflict of interest.

Acknowledgements

Not Applicable

Nomenclature

CLSD	Cattle's lumpy Skin Disease
CNN	Convolutional Neural Network
DFRCN	Deep full resolution convolution network
ELM	Extreme learning machine
FC	Fully Connected Layer
HE	Histogram Equalization
KNN	K Nearest Neighbor
LCCHIV	local color-controlled histogram intensity values
RIO	Region of Interest
ReLu	Rectified Linear Units
SVM	Support Vector Machine
QSVM	Quantum-enhanced Support Vector Machine
XGBoost	Extreme Gradient Boosting

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