
ISSN: 2321-2152
IJMECE
International Journal of modern electronics and communication engineering
E-Mail
editor.ijmece@gmail.com
editor@ijmece.com
www.ijmece.com

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

Detecting Lumpy Skin Disease in Cattle using Machine Learning with Deep Feature Extraction Techniques

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Abstract— Lumpy's disease is a viral infection that has recently spread from Africa to the Middle East, Asia, and parts of Eastern Europe, affecting cattle. Fever, excessive salivation, excessive tearing, and the presence of visible nodules on the skin are all signs of this infectious disease. For a diagnosis, one can employ PCR testing, viral isolation, and histopathology analysis. The disease's prevalence in the population is currently a major worry. A prompt and accurate diagnosis is essential because there are many different diseases that can harm animals. Infected cattle suffer irreparable damage from the Neethling virus, which causes laminitis simplex virus. The condition can lead to infertility, stunted growth, miscarriages, decreased milk production, and, in the worst case scenario, death. For feature extraction and machine learning algorithms for disease detection, the proposed solution makes use of the VGG-16, VGG-19, and Inception-v3 frameworks. When tested on a dataset and compared with sophisticated approaches like KNN, SVM, NB, ANN, and LR, the strategy demonstrates notable gains in feature extraction performance.

Keywords—Veterinary medicine, animal disease diagnosis, machine learning, skin conditions in bovines, scaly skin disease (LSD), and footling virus are all examples of viral infections in cattle.

I. INTRODUCTION

The health of an animal depends heavily on its skin. The virus that causes lumpy skin disease (LSD) in cattle is mostly transmitted by insect bites. In addition to a high temperature, runny nose, enlarged lymph nodes, and excessive tearing, the condition is characterized bylargenodulesthatgrowalloverthebody. Since its discovery in Egypt, LSD has mostly been found in Africa, Russia, Egypt, Oman, and India. Transmission of the virus may occur by bites from infected insects, but it can also spread through contaminated milk, semen, saliva, nasal secretions, or skin sores. Unfortunately, antiviral medications cannot be used to treat LSD specifically. Wound management for the treatment of skin lesions is part of the current sickness treatment approach that focuses on supportive care. In order to avoid secondary infections such as pneumonia, The use of sprays and medicines is another example of a prophylactic measure. Comparing LSD-affected animals to healthy, uninfected cows is shown in Figure 1.

Fig1.ImagesofLumpySkinandNormalSkinin cows

Laughing cow disease (LSD) is a contagious viral illness that may kill cows. Nodules appearing on the skin or other parts of the body are a telltale sign. The condition is often made worse by secondary bacterial infections. Once restricted to southern and eastern Africa, LSD began to spread northwest over the continent in the 1970s, eventually reaching sub-Saharan West Africa. In 2000, the disease made its debut in a number of Middle Eastern nations; by 2013, it had spread to Turkey and other Balkan countries as well. China, Bangladesh, Georgia, and Russia are among the countries where LSD has recently appeared. The rapidity with which it has spread across different regions has raised concerns throughout the world. Specifically, the Western Hemisphere, Australia, and New Zealand have not yielded any LSD records.

Close relatives of the LSD-causing virus include the sheeppox virus. The illness may present as isolated individuals or as widespread outbreaks. New infection hotspots often emerge in areas that were previously unaffected by the disease. While it is possible for LSD to occur in winter, it is more common during the summer months when it rains, particularly in low-lying areas near bodies of water. Because of the ineffectiveness of quarantine efforts in stopping the spread of LSD, biting insects are thought to be mechanical carriers for the drug. However, outbreaks have happened in places where the presence of insects was not anticipated. The ability to physiologically transmit the virus has been shown via experimental study on three species of hard ticks native to Africa.In addition, in laboratory conditions, contaminated saliva may transmit the illness, suggesting that direct contact might be a transmission strategy. Some animal species may help the illness survive, but in Africa, it is believed that African buffalo act as maintenance hosts.

Issues with Sagging Skin Lumpy skin disease (LSD) is a viral illness that ticks, mosquitoes, and some flies carry to cattle. Signs of the sickness include fever and skin nodules; it may be fatal, particularly in calves that have never had any kind of exposure to the virus. Vaccination and culling diseased animals are effective control measures that may halt the spread of the virus. In regions where it is often used, LSD has a substantial effect on the economy. In 2012, the disease started to spread from the Middle East into southeast Europe, hitting on Balkan states and EU members including Greece and Bulgaria, after first being found in numerous African countries. A well-coordinated vaccination campaign has helped to control the spread in certain regions. By the 1970s, LSD had expanded northwest into sub-Saharan West Africa, having previously only been seen in southern and eastern Africa. Beginning in the Middle East in the year 2000, the disease expanded to Turkey and the Balkans in 2013. Concerns over the rapid worldwide spread of the virus have intensified in light of recent reports of first-time illnesses in countries such as Russia, China, Bangladesh, and Georgia. The good news is that the Western Hemisphere, including Australia and New Zealand, has not yet discovered any LSD.

Several methods are used to diagnosis the virus, including polymerase chain reaction testing, viral isolation, and histopathology. The development of noticeable skin lesions, excessive tearing, drooling, and fever are all instances of clinical signs. While attenuated vaccinations may aid in epidemic containment, further bacterial infections sometimes worsen symptoms and make treatment more challenging.

Lumpy skin disease in cattle: what causes it and how it manifests

Loudskin disease (LSD) is caused by a virus that is closely related to the sheeppox virus. Epidemics or isolated cases of the disease are possible. Sometimes, fresh outbreaks might happen far away from where the virus first started. Although LSD is more common in the summer, it may also occur in the winter, especially in low-lying areas near water sources.

The idea that biting insects serve as mechanical vectors is often advanced when quarantine restrictions fail to limit the spread of LSD. Even Despite this, reports of epidemics have been made in contexts where the presence of insects appeared quite unlikely. The virus may be physiologically transmitted by three native hard tick species of Africa. Experimental evidence also shows that saliva infected with the virus may spread the illness, which further implies that physical touch might possibly play a role in transmission. It is believed that the virus is reservoir-hosted in African buffalo, however other animals may also play a role in the spread of the illness.

• Clinical Results for Cattle's Lumpy Skin Disease Cattle with lumpy skin disease (LSD) may exhibit symptoms such as hypersalivation, excessive tearing, nasal discharge, and fever. Approximately half of susceptible animals may experience these symptoms before the disease's signature skin eruptions appear. LSD incubates for four to fourteen days.Firm to the touch, the skin nodules are round, somewhat raised, and well-defined. It hurts. In addition to influencing the whole skin layer, these nodules may also grow on the mucous membranes of the gastrointestinal, respiratory, and vaginal tracts. It is also possible for nodules to develop on the muzzle, within the mouth, or in the nasal passages. A solid mass of tissue, either creamy-gray or yellow in appearance, is contained inside the nodules. Typical regional lymph node swelling might occur, and edema can form in areas including the legs, udder, and brisket.Extreme sloughing and purpuration of the skin might be a symptom of a secondary illness. Because of this, the animal may become very undernourished and eventually have to be put down. In time, the nodules may rupture or simply disappear, leaving behind visible, raised areas known as "sit-fasts" that stand out from the rest of the skin. These patches will peel off with time, leaving healed wounds that will eventually turn into scars.Morbidity rates with LSD vary from 5% to 50%, whereas death rates are often moderate. However, the disease causes significant economic losses due to decreased milk production, unhealthy animals, and scarring that makes skins unmarketable.• Recognizing Bovine Lumpy Skin Disease There is a less severe illness caused by bovine herpesvirus 2 that might be difficult to distinguish from lumpy skin disease (LSD), which is a different condition altogether. A frequent sign of pseudo-lumpy skin disease, also known as bovine herpes mammillitis in certain regions, is lesions on the teats and udder, however the clinical symptoms of the two illnesses might be comparable. Although the severity of pseudo-lumpy skin disease is often lower than that of true LSD, a proper diagnosis requires the isolation and identification of the specific virus responsible. In early skin lesions, the poxvirus responsible for LSD may be identified by electronmicroscopy. Importantly, PCR testing can differentiate between the two diseases. Importantly, another illness called Dermatophilus congolensis may also produce skin nodules in cattle, further complicating the diagnosis. • Care for and Prevention of Lumpy Skin Disease in Cattle Lumpy skin disease (LSD) has recently extended beyond its native African boundaries, which is causing major concern. Quarantine measures have shown only a moderate level of success in containing the illness. Among the several potential methods of control, attenuated viral immunization has shown the greatest promise in stopping the spread of LSD in the Balkans. It is sometimes not possible to treat each affected animal individually owing to the vast number of animals in a herd, even if thorough nursing care and the administration of medications to manage subsequent illnesses are suggested.

II. RELATEDWORKS

Acute or subacute sickness in water buffalo and cattle may be caused by the lumpy skin disease virus (LSDV), which poses a severe threat to the livestock sector. According to Namazi and Khodakaram Tafti (2021), although all cattle breeds are vulnerable to infection, it is more common in young calves and cows who are close to their peak milk output. As a member of the capripoxvirus genus, LSDV is a double-stranded DNA virus. Crucial clinical markers include fever, loss of appetite, obvious decrease in milk production, enlarged lymph nodes, and the rapid emergence of hard, slightly raised skin nodules after the first signs of fever. The most common method for confirming LSDV infection, while there are others, is traditional or real-time PCR (polymerase chain reaction) testing (Namazi and Khodakaram Tafti 2021).

According to von Backstrom (1945), the first documented incidence of LSDV occurred in Zambia in 1929. Africa, the Middle East, Central Asia, Southeast Europe, and, more recently, South Asia and China have all seen the virus's slow but steady spread. Several African nations, as well as Turkey, Saudi Arabia, Iraq, and Syria, are now experiencing the illness's extensive spread across the Middle East (Rocheetal.2020). High fever and secondary mastitis caused a precipitous drop in milk production, which in turn devastated the economies of the affected regions, making LSDV a major economic drag. Disease has many negative consequences, including animal mortality, hide damage, stunted beef cattle development, abortion, infertility (both temporary and permanent), and medical costs (Alemayehuet al., 2013; Namazi and Khodakaram Tafti 2021). While some insects and other arthropods that feed on blood are the most common vectors for the lumpy skin disease (LSDV) virus, it may also infect humans via contaminated food and water. As an infection progresses, the virus may be transmitted by saliva, nasal secretions, and sperm (Spryginetal.2018; Tuppurainenetal. 2017). Environmental considerations are vital in the transmission of the illness since climate greatly affects the survival of these vectors. Warm and humid weather, especially in areas with seasonal rains that boost vector populations, and the introduction of new animals to a herd substantially increase the risk of LSDV transmission. It's also possible that the virus may move further depending on the wind's direction and strength (Chihota et al. 2003). Multiple meteorological and geographical characteristics have been shown to correlate directly with LSDV outbreaks, according to studies. According to various studies, including those by Althamis and VanderWaal (2016), Allepuz et al. (2019), Machado et al. (2019), Molla et al. (2017), Sprygin et al. (2018), and Tuppurainen and Oura (2012), the following factors can be used to either predict or impact the occurrence of the disease: temperature, precipitation, land cover, humidity, and wind speed The advent of new technologies and analytical tools, such as bigdata, remote sensing, and Earth observation, has completely transformed the field of digital Earth science. These devices now monitor and characterize Earth's changing climatic systems by making use of massive spatiotemporal datasets (Kovacs-Györi et al., 2020; Yang et al., 2017).

Machine learning (ML) has become a vital tool for intelligent analysis, synthesis, and visualization of environmental and geographic data. As more and more large data sources have been available, ML approaches, particularly deep learning, have grown in popularity (Xu and Jackson 2019). For pattern discovery in complex and sometimes unmanageable datasets, these approaches leverage general-purpose learning algorithms (Bzdoketal.2018). The use of machine learning techniques is becoming more prevalent across all stages of environmental data mining, including exploratory spatial data processing, decision-driven mapping, and the modeling of spatial-temporal patterns. Specifically in the realm of large data research, machine learning techniques are progressively supplanting traditional geostatistical methods (Kanevski et al. 2008). While using ML approaches, precision and efficiency are of the utmost importance throughout the data preparation, analysis, and interpretation processes (Kanevski et al. 2008).Machine learning (ML) methods have been used in several research to predict the spread of infectious illnesses in humans and animals by analyzing geographical and meteorological data For instance, Wang et al. (2015) developed a feed-forward back-propagation neural network model to forecast the weekly incidence of infectious diarrhea cases in Shanghai, China, using meteorological data as predictive inputs. Neural networks, support vector regression, and random forest regression are examples of traditional multiple linear regression models; nevertheless, their research shows that non-linear models perform better. When tested against a variety of performance metrics, neural networks consistently outperformed the others. Similarly, Malkietal. (2020) examined many ML regressor models to predict the number of COVID-19 confirmed cases and fatalities in various countries. The K-nearest neighbors (KNN) regressor outperformed all others in predicting confirmed instances of COVID-19, however the decision tree technique yielded the best results for predicting COVID-19 mortality rates.

Using data obtained from 11 US pastured chicken farms between 2014 and 2017, Goldenetal.(2019) analyzed the soil and feces. Using meteorological factors such as temperature, wind speed and direction, humidity, and precipitation, they developed gradient boosting machine and random forest models to predict the frequency of Listeria spp. in these samples. When it came to fecal data, the AUC (Area Under the Curve) performance scores for the random forest and gradient boosting models were 0.905 and 0.855, respectively.
To predict global outbreaks of African swine disease, Liangetal.(2020) used bio-climatic parameters and machine learning approaches in a separate research. The random forest method outperformed its competitors with an accuracy rating of 80.4% when tested on a dataset that included all predictive factors. With an accuracy rate of 76.02%, the support vector machine method performed remarkably well when applied to a subset of data that only included crucial weather characteristics.
The accuracy of forecasts for Pestedes Petitsruminants (PPR) outbreaks varied from 47.8% to 99.6%, according to Niu et al. (2020), who used a variety of machine learning algorithms. Foundational for these forecasts were height data and bioclimatic factors. Among the methods investigated, the random forest model had the highest accuracy when applied to a test dataset that contained data from three non-training nations.

To the best of our knowledge, no prior research has used geographical and meteorological data to construct prediction models for the presence of the Lumpy Skin Disease Virus (LSDV). This research considered the important role of insects in the spread of LSDV and their dependence on environmental and geographic factors in order to develop prediction models using state-of-the-art machine learning methods. From 2011 to 2021, these models project the incidence of LSDV in countries with a recorded history of the illness by analyzing crucial meteorological and geographic variables.

III. Proposed Architecture & Methodology

Because no publicly available dataset exists specifically for lumpy skin disease in cattle, it is essential to create a custom dataset. The dataset with bumpy skin is sourced from veterinary facilities that are prevalent in our region. For this reason, it would be possible to gather 80-100 photographs. Methods for Pre-processing: Image pre-processing is a crucial first step in preparing pictures for model training and inference. Resizing the images, changing their orientation, and conducting color restorations are all part of this process, which aims to preserve consistency and boost the model's accuracy. Training and Initial Categorization: In this study, we use the image-net dataset to train three famous convolutional neural network (CNN) architectures: VGG16, VGG19, and InceptionV3. We choose these models because they've shown promise in classification tasks across several computer vision domains, including medical image analysis that relies on transfer learning. When tested on our dataset and compared with other state-of-the-art methods, these

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

models show remarkable efficacy in feature extraction.

A. The Suggested Method

Fig2.ProposedMethod

Figure 2 depicts a system architecture that uses machine learning approaches to classify input photos of cow skin. Let me give you a detailed breakdown: On the left side of the screen, you'll see two inputs labeled "Web Camera" and "Images Samples." These are the sources of input. The input is comprised of photos of the cow. Photos of cow skin taken by the webcam are sent into the machine learning model in real-time. This is PowerSupply: An external power source powers the camera and processing units, among other components of the system. Computer-Aided Design (CAD): Input photos (from the camera or samples) are evaluated using machine learning algorithms, which are the core part. The machine learning model receives input photographs from the samples as samplesInputImage. o Image Processing: In order to enhance feature extraction, the input photographs are likely enhanced, resized, or cleaned after processing. o ClassifyCowSkinImages: After analyzing the photos, the machine learning model can distinguish between different cow skin patterns, such normal and sloppy. The results of the classification, such as the detection of patterns or skin diseases on the surface of the cow, are shown in the inspected and showed end product. An image-based architecture that relies on machine learning aims to The objective of this classification task is to recognize images of cow skin using data collected from previously collected samples or from a live webcam feed. The system integrates image processing, classification, and power supply to achieve the target outcome.

Algorithms

4. Logistic Regression
One statistical model that uses a logistic function to describe a binary dependent variable is logistic regression. It determines what percentage of inputs belong to certain classes.

$$h_\theta(x) = \frac{1}{1 + e^{-\theta^T x}}$$

• The Bayes
The Naive Bayes classifier employs probability, which is derived from Bayes' Theorem. The characteristics are presumed to be conditionally independent based on the class designation.

$$P(C|X) = \frac{P(X|C)P(C)}{P(X)}$$

•`K-NearestNeighbors (KNN)

One kind of non-parametric learning method is KNN, which is instance-based. In order to categorize new instances, it employs the majority class of the k closest neighbors in the training set.

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_i^{(k)} - x_j^{(k)})^2}$$

• SVM, or Support Vector Machine
Finding the hyperplane in the feature space that best separates the classes is the goal of a supervised learning method known as Support Vector Machines (SVM). The objective is to maximize the difference between the two groups.

$$w^T x + b = 0$$

• ANN, or autonomous neural networks
An ANN is a model that takes its cues from a biological neural network. The activation function is applied by each layer of the network's neurons, which calculate the weighted sum of their inputs.

$$z = w^T x + b$$

VI. Results And Discussions

A: Training

Classification models vary in how they handle the information, which in turn reveals distinct patterns. Logistic regression does a terrible job with a 45.45% accuracy rate; it incorrectly labels all samples as

ISSN 2321-2152
www.ijmece.com
Vol 13, Issue 2, 2025

"lumpy" and fails to forecast any instances of the "normal" class. As the "normal" class has no accuracy, recall, or F1-score and the "lumpy" class has a high recall, the performance is clearly skewed towards the majority class. On the other hand, with an accuracy of 81.82%, Naive Bayes is the best performer. It finds a nice compromise between the two classes, with great accuracy, recall, and F1-scores for both "lumpy" and "normal," showing that this model accurately captures the underlying distribution. At 54.55% accuracy, K-Nearest Neighbors (KNN) does rather well. On the other hand, it struggles to accurately categorize the minority group ("normal"), demonstrating a compromise between recall and accuracy, particularly for the "normal" group. Just like this, Support Vector Machines (SVMs) aren't great at generalizing and overfitting to the majority class ("lumpy"), which means they don't do well with the "normal" class. Still, it gets 54.55% of the way there. In contrast, the Artificial Neural Network (ANN) outperforms all other models with an impressive accuracy of 90.91%. When testing for "lumpy" and "normal," it shows balanced performance in terms of recall, accuracy, and F1-scores. With only a single case of incorrect classification, ANN proves to be a reliable and suitable choice for this dataset. In the end, ANN is the best model for this classification task. The analysis is summarized in Table. To evaluate the performance of various classifiers in diagnosing lumpy skin conditions, the ROC (Receiver Operating Characteristic) curve is used, as illustrated in figure 3. According to the ROC curve, the best performance in Lumpy's kindis illness identification was achieved by the MLP$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n}(x_i^{(k)} - x_j^{(k)})^2}$sian Naive Bayes on this dataset.

TABLEI.INTERPRETATIONOFALGORITHMSTRAINED

Model	Accuracy	Precision(lumpy)	Recall (lumpy)	F1-Score (lumpy)	Precision(normal)	Recall (normal)	F1-Score(normal)
Logistic Regression	0.4545	0.45	1	0.62	0	0	0
Naive Bayes	0.8182	0.71	1	0.83	1	0.67	0.8
K-Nearest Neighbors	0.5455	0.5	0.8	0.62	0.67	0.33	0.44
Support Vector Machine	0.5455	0.5	1	0.67	1	0.17	0.29
Artificial Neural Network	0.9091	0.83	1	0.91	1	0.83	0.91

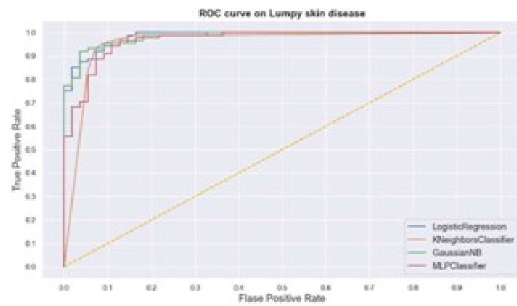

Fig3.ROCoflumpyskin disease

Depending on the situation, the other models—especially K- Nearest Neighbors—may be less ideal but still useful.

Fig4.ROCofnormalcowimages

Figure 4 shows a Receiver Operating Characteristic (ROC) curve comparison of different classifiers' performance on common cow pictures. All classifiers perform admirably in terms of classification accuracy, with low false positive rates and high true positive rates. Red: the MLP Classifier, and blue: the most consistent curve. Even if its curve is more varied, GaussianNB still does a good job. The blue Logistic Regression, in contrast, appears to possess.

V. CONCLUSION & FUTURE SCOPE

Machine learning techniques for lumpy skin disease detection using cow skin photos were compared and the results show that: On the basis of accuracy, precision, recall, and F1-score, the best performing models were Gaussian Naive Bayes and Artificial Neural Networks (ANN). Using the ROC curve, we additionally verified these models; MLPClassifier (ANN) and Gaussian Naive Bayes were the top two.
• While SVM and Logistic Regression did OK overall, they had trouble with unbalanced data and had worse recall and accuracy for the "normal" class.
• When compared to the best-performing models, K-Nearest Neighbors (KNN) had poorer accuracy and precision, especially for the minority class ("normal"), and it was less successful in distinguishing between classes.

Based on these results, ANN is the best classifier to use when looking for lumpy skin diseases. This application is well-suited to ANN because to its high accuracy in predicting both classes and its capacity to handle complicated connections in the data. Also, when computing performance is paramount, Gaussian Naive Bayes offers a simpler method that is just as successful.

1. Better Data Augmentation: To tackle the class imbalance and enhance model performance, it is recommended to augment the dataset with more labelled pictures, particularly for the minority class ("normal").
2. Using Pre-trained Models for Transfer Learning: To improve the model's capability to detect fine-grained changes in cow skin texture, it might be helpful to use transfer learning with sophisticated deep learning models like as VGG19, ResNet, or Inception. These models have the ability to extract features for illness categorization more effectively.
3. Synchronization with Real-time Systems: Automatic disease detection systems for cattle farms may be created by the integration of real-time monitoring with effective deep learning models and image capturing devices (like webcams).
4. Multi-class Classification: The model might be made more adaptable if it could be extended to identify different skin disorders in cows, not only lumpy skin disease. Training the model to handle several classes and collecting more varied datasets would be necessary for this.

To sum up, existing models are quite good at spotting lumpy skin illness, but there's room for improvement in terms of performance, data availability, and scalability that might lead to practical use of the solution in the future.

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