International Journal of Engineering Trends and Technology
ISSN: 2231–5381 / https://doi.org/10.14445/22315381/IJETT-V72I9P106

Volume 72 Issue 9, 67-77, September 2024

Original Article

Utilizing Extreme Learning Machine for the Diagnosis of Lumpy Skin Disease in Cattle

Goddeti Mallikarjun[1], V.A. Narayana[2]

[1]*Department of CSE, Research Scholar, Research Centre CMRCET, JNTUH, Telangana, India.*
[2]*Department of CSE, Professor, CMR College of Engineering and Technology, Telangana, India.*

[1]*Corresponding Author : goddeti.mallikarjun@gmail.com*

Received: 10 April 2024 Revised: 09 August 2024 Accepted: 17 August 2024 Published: 28 September 2024

Abstract - *Lumpy Skin Disease poses a remarkable threat to livestock, underscoring the urgent necessity for accurate diagnostic methodologies to enable timely intervention. The profound economic ramifications of LSD further underscore the importance of efficient diagnosis. In this context, Artificial Intelligence (AI) emerges as a transformative solution, pivotal in providing swift detection capabilities. Rapid identification of LSD not only mitigates economic burdens but also hinders the disease's spread within herds. A pioneering approach involves the utilization of Extreme Learning Machines (ELM) in tandem with VGG16 for feature extraction, tailored explicitly for LSD diagnosis. This strategy is adept at discerning intricate patterns in disease manifestation, achieving a good accuracy rate of 96.5%. The model's effectiveness is evident in its ability to differentiate between infected and healthy cases with high precision, recall, and F1 score metrics, highlighting its reliability as a dependable tool for accurate LSD diagnosis and intervention. This advancement significantly contributes to the overall health and economic stability of livestock populations, offering a promising avenue for combating the challenges posed by LSD outbreaks.*

Keywords - *Lumpy Skin Disease, Extreme Learning Machine, Convolutional Neural Network, VGG16, Hyperparameter.*

1. Introduction

Insect bites primarily facilitate the transmission of Lumpy Skin Disease (LSD), with mosquitoes and flies acting as the primary parasite vectors. The aforementioned method of transmission plays a crucial role in the spread of the illness. Many notable symptoms, such as pyrexia, the formation of skin nodules, and the development of cutaneous ulcers, facilitate the clinical diagnosis of LSD [1]. The cattle business faces significant risks from LSD because of the presence of elevated body temperature and the development of skin nodules, which are distinctive features of this condition. The first documentation of Lumpy Skin Disease (LSD) in India occurred in 2019, with its origins traced back to the state of Gujarat and subsequent countrywide dissemination. The effect of LSD in India is significant, affecting more than 2.4 million cattle and causing a catastrophic loss of 110,000 bovine lives. The current pandemic has significant economic implications, including reduced milk output and the implementation of mobility restrictions [2]. The implementation of timely diagnosis and treatment methods is crucial to effectively managing epidemics of LSD. Proactive measures, such as the application of insect repellents and the use of bed nets, are equally important in reducing the spread of diseases. These preventative methods are especially important in areas where LSD remains widespread, playing a substantial role in attempts to control the illness [3, 4]. Ticks, mosquitoes, and other blood-feeding insects transmit Lumpy Skin Disease, causing protrusions in affected animals and spreading through contact with flies and mosquitoes [5]. While there is currently no precise solution available, the implementation of supporting measures, such as the administration of antibiotics for secondary infections and the application of wound dressings to reduce fly strikes, can potentially yield positive outcomes. Since its inception in Zambia in 1929, LSD has been disseminated to diverse places in Africa and other parts of the world, with recent occurrences documented in both Asia and Europe [6, 7]. Preventive measures against LSD involve implementing immunization programs and euthanizing infected animals. Extreme Learning Machines (ELM) combined with Artificial Intelligence (AI) could be used for diagnostic purposes, which could lead to faster and more accurate identification and treatment of LSD cases. Extreme Learning Machines (ELM) have the potential to effectively capture spatial hierarchies and complex information from medical pictures, making them a suitable method for diagnosing LSD [8]. Despite the advantages of ELM, it faces difficulties when confronted with tasks that include unprocessed picture data. In order to overcome this obstacle, researchers have explored the combination of ELM with integrated networks with the purpose of extracting features before classification [9]. This method takes advantage of the capability of integrated networks to store representations of image features, which makes ELM better at reading visual tasks [10]. VGG16 is one of the most reputed convolutional neural networks applied for tasks on image recognition [11]. Being complex in design, VGG16 comprises many layers of convolutional and pooling procedures that are succeeded by fully linked layers [12]. The design of VGG16 enables it to progressively get hierarchical representations of visual aspects.

This process begins with fundamental features like edges and textures and progresses towards more complex semantic elements that include complicated patterns and structures within pictures [13]. VGG16 functions by converting unprocessed pixel data into a comprehensive, multi-dimensional feature vector that encompasses important information about the image content. ELM then uses the feature vector as input for the classification step [14, 15]. These two systems work together to make classification more accurate by using VGG16's ability to pull out unique features and ELM's effectiveness in classification tasks [16]. Additionally, using transfer learning methods and adding VGG16 models that have already been trained can improve the system's ability to generalize [17]. It has not only improved the accuracy of classification but also solved all the problems associated with the use of raw picture data directly in classification tasks, thus serving to advance computer vision and pattern recognition. [18]. Since lumpy skin disease affects the majority of cattle, it is a big threat to the lives of these animals and the business of animal farming. Since hematophagous insects have become the primary transmitters of this sickness, the world absolutely requires efficiency in the prevention method and specificity in diagnostic techniques. This study, thus, offers a unique solution based on the integration of ELM with feature extraction in the form of VGG16. In turn, the rapid learning rate in ELM, as well as the improved feature extraction in the VGG16, make it an all-round AI-based diagnostic tool. The above-outlined methodology contributes not only to fast and reliable identification of LSD but also assists in early intervention, reducing the impact of the disease on cow herds and other related large businesses and livestock farmers.

Organization of the Paper: The paper is organized into multiple separate sections subsequent to the introduction. In Section 2, the literature review is explored, where existing research is combined and placed in its appropriate perspective. Section 3, Methodology, is a thorough account of the study strategy and approach. The experimental results and subsequent analysis are presented in Section 4, taking into consideration the theoretical frameworks. Moreover, the Conclusion section, namely Section 5, provides a concise overview of the significant findings obtained from the experiment and suggests potential ramifications for the respective field. The present framework provides a comprehensive examination of the subject of research, offering substantial contributions within a succinct format.

1.1. Contribution of Paper

- This study presents an innovative approach that integrates ELM into the diagnosis of LSD in cattle. The present approach demonstrates a high level of efficacy in the identification of LSD patterns in skin lesion photographs since it places image analysis as a priority above conventional techniques like PCR. Through iterative refinement, the model exhibits its capacity to adapt to the evolving dynamics of illnesses, thereby enhancing its diagnostic precision over time.
- The use of AI functionalities inside this ELM model enhances the accuracy and dependability of LSD diagnosis, presenting a potentially effective approach for disease control. This achievement is especially important in agricultural economies such as India, as it highlights the vital role of AI in protecting food security and the livelihoods of farmers worldwide.

2. Literature Review

The diagnosis of LSD with the application of CNNs has been very effective, which is evidenced by the impressive accuracy rates portrayed in different studies. CNNs are especially good because they can autonomously learn complex features from image data, which is critical to the precise identification of diseases. Genemo et al. evaluated further sophisticated models of CNN, such as DenseNet201 combined with RCNN and several classifiers: Naive Bayes, Support Vector Machine, Fine K-Nearest Neighbors, and Extreme Learning Machine. The accuracy obtained in this full model was 90.12%, with the Extreme Learning Machine as the best classifier. The study also pointed out the advantages of integrating the various techniques for feature extraction and presented a wholesome overview of LSD diagnosis using image data. This means that such an integrative approach will allow further studies on the optimization of feature extraction to realize improved diagnostic accuracy. On the same note, Lake et al. employed a CNN-based technique and realized a relatively respectable 95% accuracy in the diagnosis of LSD. Their approach underscored the proficiency of deep learning in independently extracting spatial hierarchies that were key to identifying complicated patterns for a disease. It also recognized some challenges associated with CNNs, such as issues of interpretability and computational demands. In spite of that, the high accuracy realized shows a promising role of CNNs in advancing diagnostics for LSDs, especially capturing minute features that conventional methods might otherwise miss. Rony et al. applied well-known CNN architectures like Inception V3 and VGG-16 and achieved an accuracy of 95% in LSD diagnosis. Their study pointed out that the power of the CNNs in automatic feature learning from images, which is a must for any effective image analysis, became very useful. It has been underlined that despite the high degree of computational complexity and still rather limited interpretability of these architectures, their effectiveness has already been proven in several areas, including veterinary diagnostics.

Rai et al. tested the flexibility of CNN feature extraction methodologies using VGG16, VGG19, and Inception V3 with multiple classifiers. Their methodology delivered quite an impressive accuracy of 92.5%, wherein coupling ANN with Inception V3 turned out to be the most efficient. This study further exemplifies the flexibility of the CNN model in extracting complex disease patterns; it should be possible to adapt models for any diagnostic task. In all of these studies, there are common challenges: computational intensity of CNNs, good-quality training data, and limited interpretability of deep learning and machine learning models. To this end, computational efficiency needs to be balanced against model transparency and the prevention of overfitting. Such considerations in this line will be central to further advances in applying CNN-based methods for the accurate diagnosis of lumpy skin disease.

2.1. Problem Statement

Artificial intelligence (AI) effectively tackles the difficulties related to the identification of lumpy skin disease (LSD) through the provision of unbiased, dependable, and expeditious diagnostic capabilities. By utilizing pattern recognition and machine learning methods, artificial intelligence reduces the occurrence of incorrect diagnoses and quickly detects LSD, therefore enhancing illness management. The utilization of remote capabilities diminishes reliance on infrastructure, while the implementation of automated operations reduces expenses and resource demands. In essence, AI improves disease management efforts by decreasing the spread of diseases, minimizing financial losses, and mitigating trade consequences. Additionally, it strengthens veterinarians' capabilities and expertise.

2.1.1. Subjectivity

The use of AI's objective algorithms and machine learning techniques helps to reduce the inherent subjectivity in diagnosing LSD in animals through visual inspections. AI enhances the accuracy and uniformity of diagnoses by integrating data and recognizing patterns, thereby minimizing errors associated with human subjectivity and improving sickness management.

2.1.2. Misdiagnosis

AI mitigates misdiagnosis in LSD by detecting unique patterns, acquiring knowledge from data, and integrating various sources. The utilization of validation methodologies and decision support systems has been shown to improve the precision of differentiating LSD from other similar diseases, thereby reducing errors and ensuring the implementation of suitable treatment and control strategies. Budgetary and resource constraints: AI also mitigates the budgetary and resource constraints linked to LSD testing through the provision of remote and automated diagnostic alternatives. AI-driven platforms diminish dependence on tangible laboratory apparatus, facilitating dispersed testing. Automated methods for sample collection and analysis enhance operational efficiency through the reduction of specialist personnel and equipment requirements, resulting in a decrease in overall expenses.

3. Methodology

The Extreme Learning Machine (ELM) technology is used to diagnose lumpy skin illnesses, with a specific focus on nodular skin lesions. These lesions are important because they have unique and easily recognized characteristics that are essential for network learning. The lesions display pathognomonic characteristics, which are well-suited to the interpretability benefit of ELMs. This enables the model to accurately identify and understand complex patterns related to the existence of the disease. The non-invasive nature of image-based diagnosis is well-suited for the clinical visibility of nodular lesions, rendering them optimal focal sites for the model. By utilizing this attribute in the ELM, the model guarantees that it concentrates on prominent aspects, facilitating precise and effective detection, particularly during the first phases of the disease.

The preprocessing stage subjects the raw image data to a series of changes to improve characteristics pertinent to nodular lesions. Enhanced the quality of the images to raise their features in such ways as contrast adjustment, noise reduction and picture standardization. In addition, the information extracted from the preprocessed images employs the use of attributes to describe characteristics, such as the nodular patterns and textures that have been deemed to be important in determining lumpy skin conditions.

The ELM architecture takes preprocessed images of diseases and their diagnosis and learns such images in the training stage. In other words, during the training process, through the parameter adjusting process, the neural network learns to recognize nodular lesions as valuable disease indicators. This involves updating steps going forward and then backwards to perform gradient computations in a bid to minimize the loss function linked with the misclassification of diseases through reorganizing the network weights.

Following the training process, the model is assessed using a distinct dataset specifically designated for testing purposes. The testing procedure entails exposing the trained network to previously unseen photos and evaluating its ability to accurately detect nodular lesions that are symptomatic of lumpy skin conditions. The model's diagnostic capabilities by analyzing performance metric indicators such as accuracy, precision, and specificity. Moreover, the interpretability of the model enables physicians to comprehend the rationale underlying its predictions, thereby augmenting trust and usability within therapeutic environments. The ELM exhibits its promise as a reliable tool for promptly and precisely diagnosing lumpy skin illness by analyzing nodular skin lesions, thanks to thorough training and testing depicted in Figure 1.

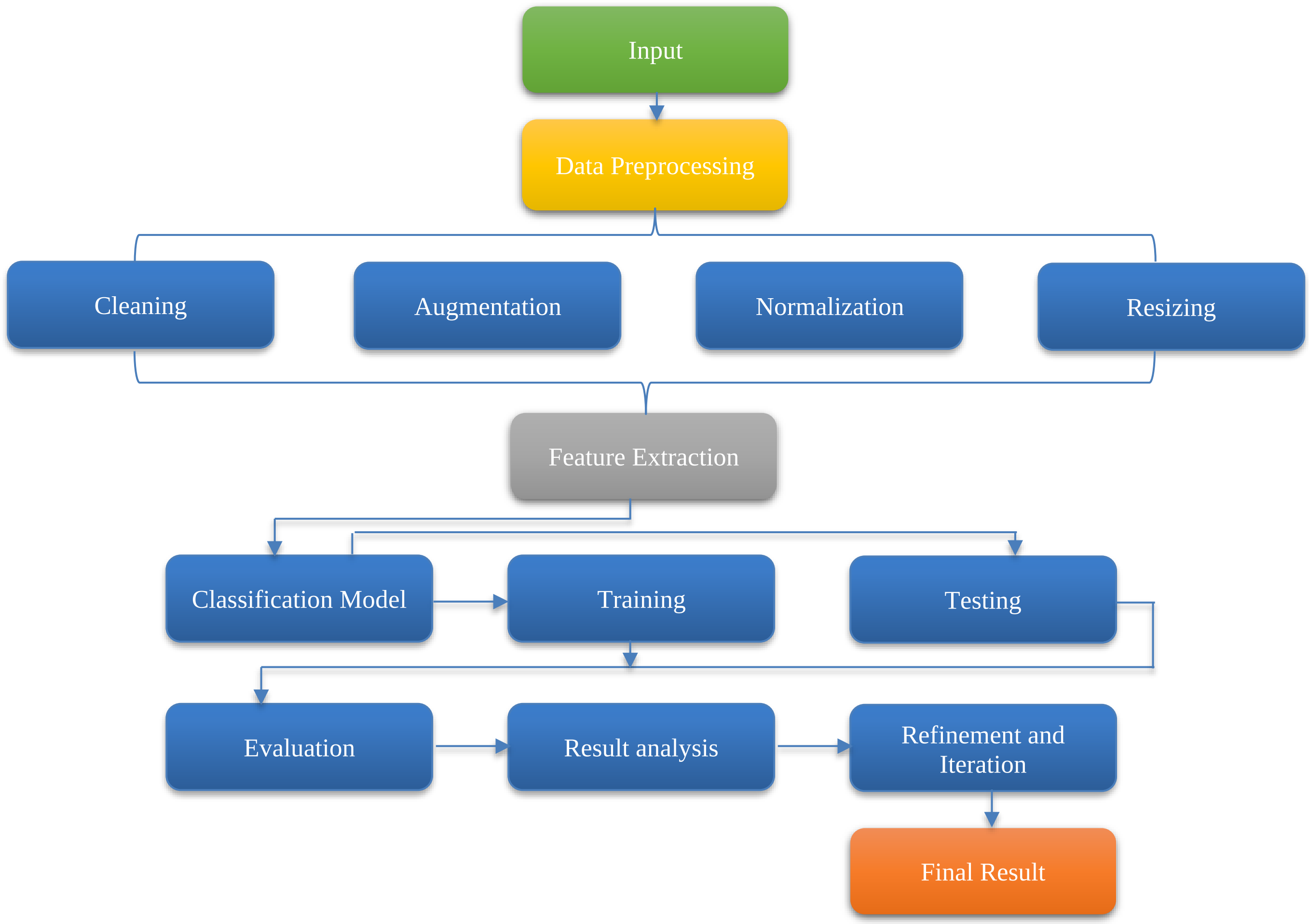


Fig. 1 Proposed methodology architecture

3.1. Data Collection

This dataset was created from various sources, including P. V. Narasimha Rao Telangana Veterinary University, veterinary hospitals, and after consultations with the practitioners of veterinary science. There are 520 RGB images in the dataset; among those, 355 images are of normal conditions, while 165 images show lumpy skin diseases. The total dataset of this varied collection is surely a very good resource for studies aiming at constructing and validating diagnostic tools and treatment methods against lumpy skin conditions. This collection affords excellent study and opportunities for discussing a wide range of photographs, both of healthy conditions and those representing pathology, hence making substantial contributions to the literature relating to veterinary medicine and livestock management.

3.2. Data Preprocessing

Data preprocessing is thus a very significant step in the preparation of the collected images to work on in order to improve the diagnostic capabilities with higher accuracy levels on identification. This will be an operation to be performed in preparation to improve the image data standard and relevance of the data to the subsequent modelling. First of all, the pictures were resized to 256×256 pixels. This resizing ensures consistency in image size across the dataset, facilitating uniform processing and analysis. Following resizing, the data undergoes image cleaning, which involves a thorough examination and elimination of artifacts and irrelevant details present in the images. Artifacts such as noise, blurriness, or anomalies that could impede the model's accurate interpretation of visual information are carefully removed. This refining process ensures that the model receives clean and reliable input data. Subsequent to image cleaning, normalization is used to standardize the pixel values for all disease and non-diseased images in the dataset. This process guarantees uniformity in pixel distributions, which is crucial for model training. Standardizing pixel values minimizes variations between images, preventing the model from being biased towards certain intensity ranges or features during training. Normalization also stabilizes the learning process and enhances the model's convergence during training. Following that are the augmentation techniques to add diversity to the dataset. Augmentation also has a perspective and images, while it discusses the act of rotating, scaling, flipping, and cropping images. All these transformations produce a new image with a changed appearance, and while doing so, they teach the model a broader range of images. This makes the model to be stronger in terms of performance and more flexible in cases of responses by using the augmented dataset for training. Augmentation also aids in mitigating overfitting by training the model to recognize features across a wider range of contexts. Through a comprehensive approach encompassing resizing, image cleaning, normalization, and augmentation, the quality of the dataset is refined. This ensures that the model receives clean, standardized, and diverse input data, laying the groundwork for robust and accurate performance in diagnosing lumpy skin disease.

3.3. Data Annotation

The dataset, consisting of 520 bovine photos, was thoroughly annotated with the aid of veterinary professionals. The photographs were then categorized into two classes: 0 for ill cattle and 1 for healthy cattle. Images in Class 0 display clinical symptoms, and annotations carefully define pathological traits for accurate identification.

On the other hand, Class 1 includes photos of cattle that are in good health, with comments that describe the anatomical components. An extensive examination was conducted on the annotation process to guarantee precise categorization, hence enabling efficient training of machine learning models. The dataset, which has been annotated through collaboration with veterinary professionals, plays a vital role in the advancement of automated illness detection algorithms for cattle. The impact of this technology extends to facilitating progress in the fields of veterinary diagnostics and livestock management, thereby improving the overall health and welfare of cow populations.

3.4. Feature Extraction

Feature extraction is a pivotal component in the field of disease diagnosis through the utilization of images, as it effectively captures vital information and patterns from unprocessed image data. Within the field of medical imaging, the process of feature extraction is employed to accentuate particular visual characteristics that serve as indicators of the disease, such as skin nodules or lesions. The VGG16 model, a widely employed convolutional neural network in the field of image classification, demonstrates exceptional proficiency in extracting hierarchical features from images. It has the capability to record a diverse array of characteristics, such as edges, textures, forms, and intricate patterns that are present in the photographs. The retrieved features play a pivotal role in representing the input images, providing machine learning algorithms with the ability to accurately differentiate between normal and pathological states. VGG16 improves the precision and dependability of disease detection by prioritizing the most distinctive attributes. This ensures that the diagnostic model is capable of accurately differentiating between persons who are in good health and those who are unwell, thereby enabling prompt intervention and therapy.

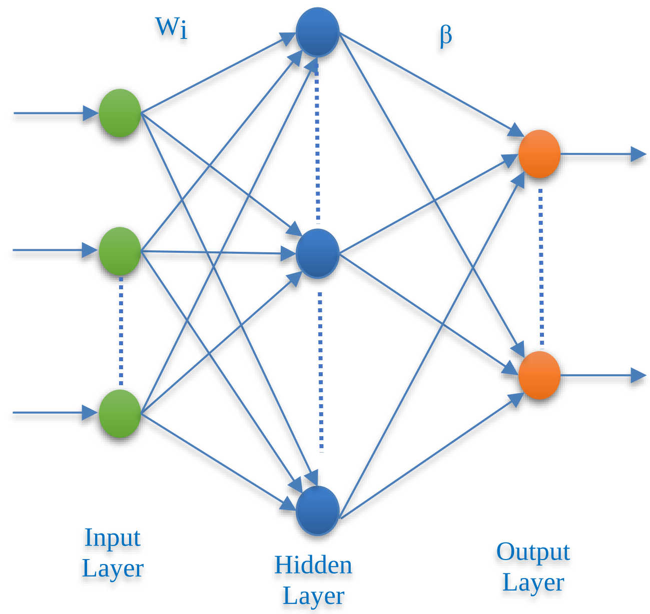


Fig. 2 Extreme learning machine architecture

3.5. Extreme Learning Machine

Extreme Learning Machines (ELMs) represent a breed of feed-forward neural networks distinguished by a solitary, hidden layer comprising randomly initialized neurons. Unlike conventional neural networks, ELMs feature fixed parameters in the hidden layer and dispense with the need for iterative training of these parameters [23]. In the architecture of extreme learning machines implemented in Figure 2, after the hidden layer is randomly set, the weights of the final layer are calculated analytically by linear regression.

3.5.1. Input Layer

- It consists of neurons where each neuron accounts for the features extracted from the data. Let x be the input data and N be the number of input neurons.
- In this, each and every neuron receives a feature from the input data; that is, xi such that i = 1 … N.

3.5.2. Hidden Layer

- It is initiated with unmethodically lying neurons, each of which has its bias bi and input weights w_{ij}, where i refers to an index representing the hidden neuron and j an index referring to the input neuro.
- The result of each hidden layer neuron, denoted as (H_i), is computed using a nonlinear activation function (f). Common activation functions include sigmoid, tanh, or ReLU.
- Mathematically, the result of this layer neuron (I) can be represented as:

$$H_i = f(\sum_{j=1}^{n} w_{ij}x_i + b_i) \quad (1)$$

3.5.3. Output Layer

- The neurons of the output layer can be related to classes or categories of the problem in case any exists, as depicted in Figure 2 below, where y is the data.
- Each y_i in this layer is some linear combination of the outputs of neurons in the 2nd layer, which are modified by βi that are the output weights.
- Mathematically, with respect to the output from this layer neuron i, this can be expressed as: - Mathematically, with respect to the output from the output layer neuron i, this can be expressed as:

$$y_i = \sum_{j=1}^{L} \beta_{ij} H_j \tag{2}$$

- The output weights β are calculated using linear regression, which can be expressed as:

$$\beta = (H^T H + C^I)^{-1} H^T T \tag{3}$$

H is the matrix of hidden layer output, T is the matrix of target output, C is the normalize parameter, and I is the identity matrix as in Equation 3. ELM consists of an input layer where features are inputted, a hidden layer with randomly initialized neurons, and an output layer where the output is calculated using linear regression based on the hidden layer output [24]. This architecture allows for efficient training and fast convergence, making ELMs suitable for various machine learning tasks.

4. Experimental Results

K-fold cross-validation is a reliable procedure that is implemented in order to determine to what extent the model is accurate and universal. It is done through the division of data sets into k subsets with nearly the same number of observations. Here, label one of the subsets with the flag of being the validation set, and the rest of the k-1 subgroups are used for training. This is done so that every subset can experience the others, being the validation set, and this is repeated k times. In 10-fold cross-validation, the data is partitioned into 10 sets, usually 90% for training and the rest 10% for implementation or testing. It tests with 9 subsets in one round. To train and evaluate in this process, employ a training set as well as a validation set in each fold. The strength of cross-validation, therefore, is that after all fold, an average of the performance indicators, for instance, the accuracy or the error rate, is calculated and determined conclusively. Consequently, it rules out all chances of overfitting or underfitting to some or the other part of the data, thereby becoming a correct measure of the model on several parts of data.

4.1. VGG16 for Feature Extraction

VGG16 can, therefore, be used as feature extraction for several machine learning tasks, such as disease diagnosis. Residing in the context of diseases such as LSD, VGG16 indeed helps as a powerful feature extractor because of its ability to extract coherent features and representations of raw Shelby, as shown in Figure 3. In the context of diagnosing lumpy skin disease, VGG16 extracts features from images of cattle exhibiting symptoms of the disease, such as skin nodules or lesions. These images are fed into the pre-trained VGG16 network, and as they pass through the network's layers, different levels of features are extracted at various depths of the network. The features extracted by VGG16 encode information about the visual characteristics of the images, capturing patterns and structures indicative of lumpy skin disease. The extracted features serve as a representation of the input images but in a more compact and informative form. Instead of directly using the raw image pixel values of the images, which can be high-dimensional and noisy, the extracted features provide a distilled representation that highlights the most relevant aspects of the images for disease diagnosis. After feature extraction by VGG16, the features are inputted into an ELM, which functions as a final predictor. ELM, a kind of feed-forward neural network, is characterized by a single hidden layer comprising randomly initialized neurons. In contrast to conventional neural networks, ELM does not necessitate iterative training and can rapidly learn the correlation between input features and output labels. By combining VGG16 for feature extraction with ELM for classification, the system can effectively diagnose lumpy skin disease in cattle. The features extracted by VGG16 capture the distinctive visual characteristics of the disease, while ELM efficiently learns to classify these features into normal or diseased categories. This approach leverages the strengths of both feature extraction and classification techniques, resulting in a robust and accurate diagnostic system for lumpy skin disease.

4.2. Training Results

Using the VGG16 for feature extraction coupled with an ELM model, a training process spanning 10 iterations was conducted. Each iteration involved training the model with 90% of the available data, sequentially incorporating the remaining 10% until all data had been utilized. Throughout the iterations, the training accuracy consistently ranged from 0.97 to 0.99, as shown in Figure 4, indicating the model's proficiency in correctly classifying the data. Additionally, the training loss, which ranged between 0.18 and 0.11, showcased the effectiveness of the model in minimizing errors during the training process depicted in Table 1.

Table 1. Training accuracy and loss of extreme learning machine

Iteration	Training Accuracy	Loss
1	0.97	0.18
2	0.97	0.15
3	0.97	0.12
4	0.98	0.15
5	0.97	0.14
6	0.98	0.13
7	0.97	0.15
8	0.98	0.14
9	0.98	0.12
10	0.99	0.11

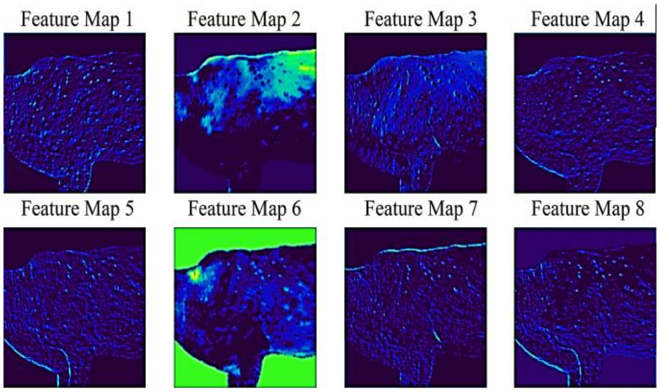


Fig. 3 Result of VGG16 as feature extraction

4.3. Hyperparameter Tuning

Utilizes an ELM with 100 hidden neurons, a ReLU is an activation function, and a regularization parameter of 0.001 is shown in Table 2. The model gains from using ReLU as the activation function since it can reduce the vanishing gradient issue and hasten convergence during training. The relatively low regularization parameter of 0.001 suggests a mild penalty for complex models, helping prevent overfitting while enabling the model to identify difficult patterns in the information. The choice of 100 hidden neurons balances model complexity and computational efficiency, enabling effective feature learning while avoiding excessive computational costs. Extreme Learning Machine (ELM) with 200 hidden neurons, a sigmoid activation function, and a regularization parameter of 0.01 are shown in Table 3. By utilizing the sigmoid activation function, the model can model non-linear relationships between features more flexibly compared to linear functions, possibly identifying complex patterns in the data. The regularization parameter of 0.01 indicates a moderate penalty for complex models aimed at preventing overfitting by constraining the model's capability to fit noise in the training data. With 200 hidden neurons, the model increases its capacity to learn intricate feature representations, potentially improving its ability to generalize to new data.

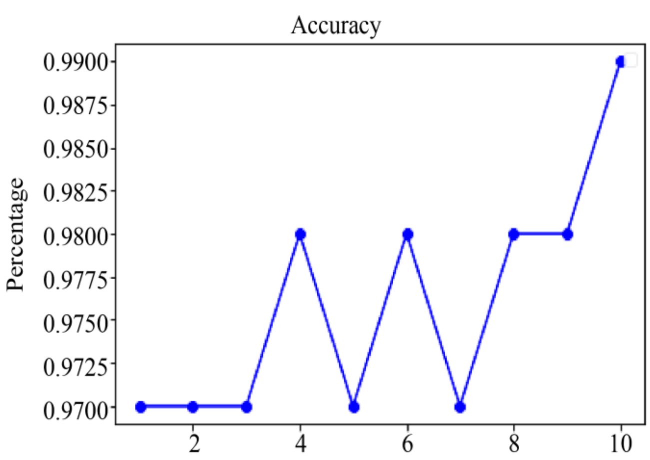


Fig. 4 Training accuracy over the batches

Table 2. Hyperparameter values (100 HN)

Hyperparameter	Value
No. of hidden neurons	100
Activation function	ReLU
Regularization parameter	0.001

Table 3. Hyperparameter values (200 HN)

Hyperparameter	Value
No. of hidden neurons	200
Activation function	Sigmoid
Regularization parameter	0.01

Table 4. Hyperparameter values (250 HN)

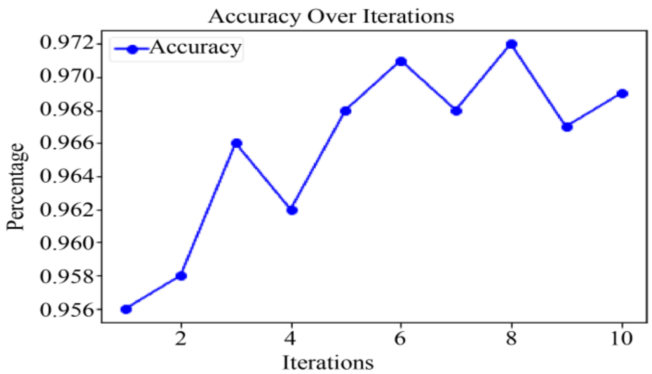
Hyperparameter	Value
No. of hidden neurons	250
Activation function	Tanh
Regularization parameter	0.1

ELM with 250 hidden neurons, using the hyperbolic tangent (Tanh) activation function, and a regularization parameter of 0.1 are shown in Table 4. The Tanh activation function offers similar properties to the Sigmoid function but is symmetric around zero, facilitating better gradient flow during training. With 250 hidden neurons, the model gains an increased ability to identify intricate connections within the data, which might allow it to discover more subtle characteristics. The regularization parameter of 0.1 indicates a comparatively strong penalty for model complexity, which may help prevent overfitting by preventing the algorithm from fitting the noise in the training data.

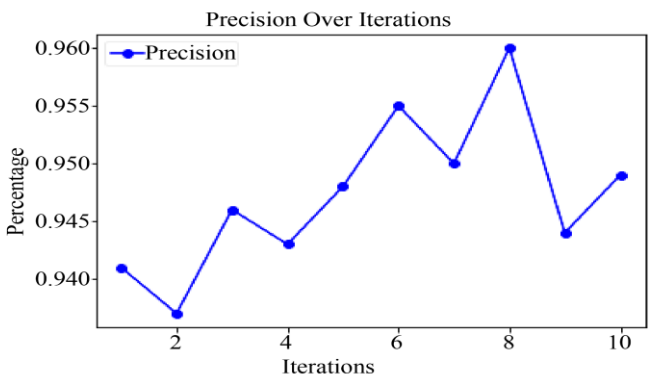
4.4. Testing Results

The testing process comprises 10 iterations, each involving training on 90% of the dataset and testing on the remaining 10%, utilizing the VGG16 model as the feature extractor. This iterative approach ensures comprehensive coverage of the dataset while robustly evaluating model performance. The average accuracy of 0.965 reflects the model's capability to accurately categorize instances, while the average recall of 0.952 indicates its effectiveness in identifying relevant instances among all true instances.

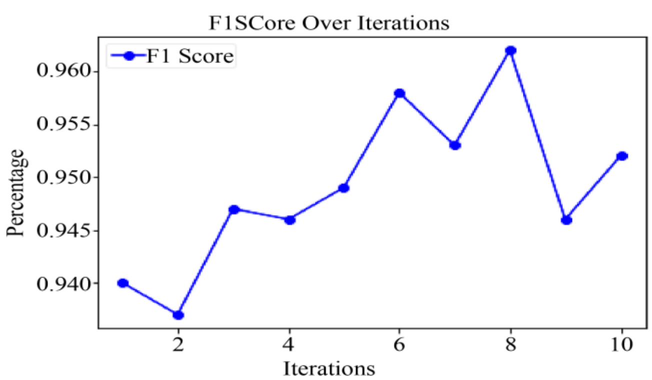
Similarly, the average precision of 0.947 denotes the accuracy with which the model can categorize positive cases, reducing false positives. The F1 score, averaging 0.949, balances precision and recall, offering a well-rounded analysis of the model's performance, as illustrated in Table 5. This iterative testing method not only ensures a thorough evaluation but also helps find problems with overfitting or underfitting across multiple iterations. This makes the evaluation of the VGG16-based model's classification abilities more reliable. The representation of accuracy, recall, precision, and F1 score over 10 iterations is depicted in Figure 5. Each metric is plotted against the iteration number using Matplotlib. The figure provides insights into the execution trends of the model during testing.



(a)



(b)



(c)

(d)

Fig. 5 Model testing results
(a) Testing accuracy, (b) Testing precision, (c) Testing f1score, (d) Testing recall

Table 5. Testing accuracy, recall, precision and F1 score over iteration

Iteration	Accuracy	Recall	Precision	F1 Score
1	0.956	0.945	0.941	0.940
2	0.958	0.938	0.937	0.937
3	0.966	0.950	0.946	0.947
4	0.962	0.950	0.943	0.946
5	0.968	0.951	0.948	0.949
6	0.971	0.963	0.955	0.958
7	0.968	0.957	0.950	0.953
8	0.972	0.966	0.960	0.962
9	0.967	0.950	0.944	0.946
10	0.969	0.956	0.949	0.952

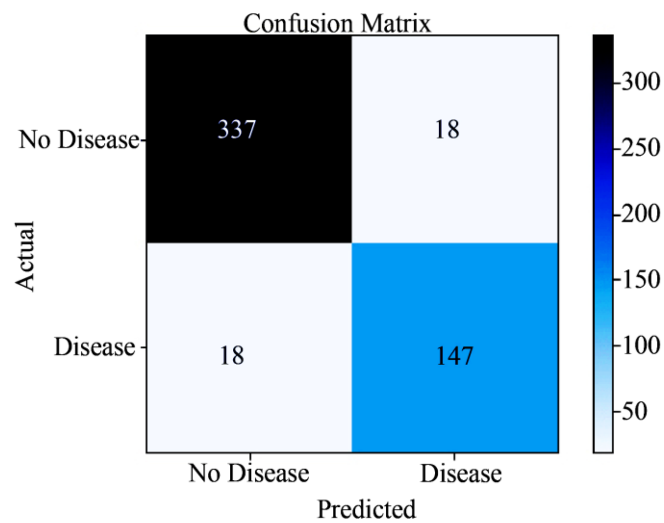


Fig. 6 Confusion matrix

4.5. Confusion Matrix

The supplied confusion matrix provides information about the model's performance after applying an Extreme Learning Machine (ELM) for classification and VGG16 for feature extraction. It presents four key values: true negatives (336.8), false positives (18.2), false negatives (18.2), and true positives (146.8), as depicted in Figure 6. These values represent instances accurately and inaccurately classified as either having or not having the disease. The significance of the confusion matrix lies in its capability to provide a detailed breakdown of the algorithm’s predictive accuracy. It enables practitioners to evaluate the deal between sensitivity and specificity. Through analysis of the confusion matrix, clinicians can make informed decisions regarding treatment plans, surveillance strategies, and resource allocation in the fight against lumpy skin disease, thereby enhancing patient outcomes and disease management.

4.6. Area under the ROC Curve

Receiver Operating Characteristic curve of the classification model performance with an area under the curve value of 0.942, as shown in Figure 7. This result depicts a deal between the true positive rate and the false positive rate achieved by the model.

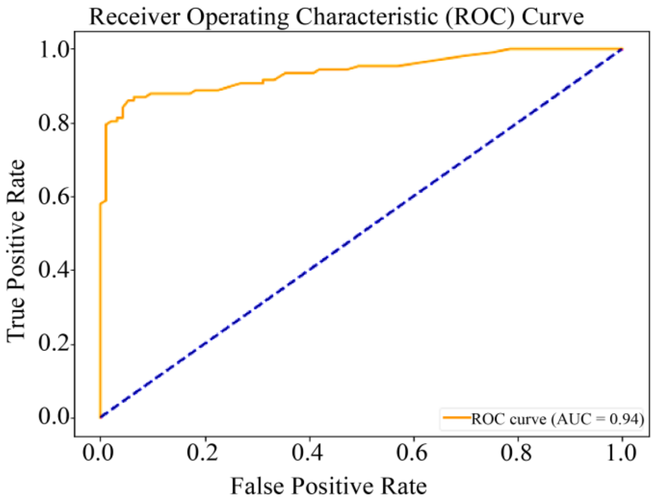


Fig. 7 Area under ROC curve

The ROC curve illustrates this balance across various threshold values, providing information on how well the model can differentiate between positive and negative cases. A high AUC value nearing 1 indicates that the model possesses outstanding discriminative capability and can accurately differentiate between diseased and non-diseased cases. This capability holds particular significance in the diagnosis of lumpy skin disease, where precise identification of affected individuals is critical for prompt treatment and effective disease management. The ROC curve and AUC provide clinicians and researchers with valuable information to evaluate and improve diagnostic algorithms, ultimately enhancing patient care and disease control efforts.

4.7. Comparing with Existing Work

The proposed model, employing an Extreme Learning Machine (ELM) with a reported accuracy of 96.5%, outperforms several existing approaches to lumpy skin disease (LSD) diagnosis. While Musa Genemo et al. achieved a commendable 90.12% accuracy using DenseNet201 and RCNN coupled with various classifiers, the proposed model demonstrates superior performance, indicating advancements in accuracy. Similarly, Lake et al. achieved a notable 95% accuracy with a CNN-based approach, highlighting deep learning's efficacy in intricate feature extraction. Despite these accomplishments, the proposed model surpasses their accuracies, underscoring its effectiveness in accurate LSD identification. Moreover, Rony et al. and Rai et al. also achieved competitive accuracies of 95% and 92.5%, respectively, with CNN architectures and diverse classifiers.

However, the proposed model exceeds their reported accuracy, indicating its superiority in LSD diagnosis, as shown in Table 6. The utilization of Extreme Learning Machines in the proposed model showcases its efficacy in handling LSD image data, providing a comprehensive understanding of the disease and offering promising avenues for future research in advancing LSD diagnostics.

Table 6. Comparing with existing work

S.no	Author	Model	Accuracy
1	Musa Genemo et al. [19]	Extreme learning machine	90.12%
2	Bezawit Lake et al. [20]	CNN (Convolutional Neural Networks)	95.00%
3	Md.Rony et al. [21]	CNN (Convolutional Neural Networks)	95.00%
4	Gaurav Rai et al. [22]	Neural network and inspectionv3	92.50%
5	Proposed Model	Extreme Learning Machine	96.50%

4.8. Result and Discussion

VGG16, as a feature extractor, is an Extreme Learning Machine that is capable of diagnosing lumpy skin diseases. Its improvement work at the preprocessing level, such as hidden nodes, types of regularization, activation functions, random seed initialization, and the like, has gradually brought it to the best learning performance and generalization balance that does not fall into overlearning. In the architectural design, each hidden layer is crucial in enhancing the features extracted by the VGG16 in a manner that only the ELM gets to see the features it needs for diagnosis.

The outcome of this has clearly shown that applying the proposed technique improves the accuracy of diagnosis, not to mention the fact that outcomes are consistent and dependable. It obtained a training accuracy of 0. 99 and a testing accuracy as low as 0. 965. The rest of the evaluation metrics were also equally good in terms of the depiction of the model performance, such as the recall and the accuracy, and the F1 score of the model was at 0. Indeed, it is almost 95, which indicates that the model has acquired the signs of LSD in the face images and has acceptable differentiation between severe and mild ones.

Looking at these results in parallel with modern trends, it may be concluded that the solution proposed here is ahead of such models as DenseNet201 or RCNN, which averages approximately 90% accuracy. In this respect, the realized improvement also redecorates ELM’s capability for processing complicated medical image data and, therefore, is still a robust tool in clinical decision-making within the sphere of veterinary sciences. It is useful to contribute to the advancement of state-of-the-art pattern recognition and, more specifically, in the application concerning disease diagnosis, as in the veterinary field, it aids in elaborating better management and treatment for animals with diseases.

These results could, therefore, be suggestive of further research opportunities with a view to improving the potential of ELM-based models anchored in medical imaging and in any other field requiring accurate pattern recognition.

5. Conclusion

The methodology holds great potential for mitigating the economic losses incurred by lumpy skin disease outbreaks. Timely and accurate diagnosis can lead to prompt treatment, reducing morbidity and mortality rates among livestock. Furthermore, by preventing the spread of the disease, farmers can safeguard their herds and minimize the economic repercussions associated with decreased productivity and trade restrictions. The combination of ELM and VGG16 presents a robust framework for diagnosing lumpy skin disease, offering a viable solution to mitigate its impact on agricultural economies and ensure the welfare of livestock populations. The utilization of an Extreme Learning Machine (ELM) in conjunction with VGG16 for diagnosing lumpy skin disease presents a promising approach with significant implications for agricultural economies. Lumpy skin disease poses a considerable threat to livestock, impacting both animal welfare and the economic viability of the agriculture sector. By employing ELM alongside VGG16 as a feature extraction mechanism, we achieved a commendable accuracy rate of 96.5%. This high accuracy rate demonstrates how well the suggested methodology works to correctly identify and diagnose the illness, allowing for prompt intervention and control measures. The integration of ELM and VGG16 not only enhances the precision of diagnosis but also streamlines the process, enabling rapid identification of affected animals.

References

[1] Somil Gambhir, Sanya Khanna, and Priyanka Malhotra, "Machine Learning Based Diagnosis of Lumpy Skin Disease," *2023 International Conference on Artificial Intelligence and Applications (ICAIA) Alliance Technology Conference (ATCON-1)*, Bangalore, India, pp. 1-5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Elavarasan Mathivanan, Kavitha Raju, and Rajaganapathy, "Outbreak of Lumpy Skin Disease in India 2022- An Emerging Threat to Livestock & Livelihoods," *Global Biosecurity*, vol. 5, no. 1, pp. 1-9, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Amit Gupta et al., "Revolutionizing Cattle Health: A Machine Learning Approach to Efficiently Predict Lumpy Disease in Cows," *2023 4th IEEE Global Conference for Advancement in Technology (GCAT)*, Bangalore, India, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Vipul Narayan et al., "Severity of Lumpy Disease Detection Based on Deep Learning Technique," *2023 International Conference on Disruptive Technologies (ICDT)*, Greater Noida, India, pp. 507-512, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Naveen Kumar, and Bhupendra Nath Tripathi, "A Serious Skin Virus Epidemic Sweeping through the Indian Subcontinent is a Threat to the Livelihood of Farmers," *Virulence*, vol. 13, no. 1, pp. 1943-1944, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[6] Neha Ujjwal et al., "Exploiting Machine Learning for Lumpy Skin Disease Occurrence Detection," *2022 10th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO)*, Noida, India, pp. 1-6, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] Wassie Molla et al., "Economic Impact of Lumpy Skin Disease and Cost Effectiveness of Vaccination for the Control of Outbreaks in Ethiopia," *Preventive Veterinary Medicine*, vol. 147, pp. 100-107, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[8] Jian Wang et al., "A Review on Extreme Learning Machine," *Multimedia Tools and Applications*, vol. 81, pp. 41611-41660, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Shan Pang, and Xinyi Yang, "Deep Convolutional Extreme Learning Machine and Its Application in Handwritten Digit Classification," *Computational Intelligence and Neuroscience*, vol. 2016, no. 1, pp. 1-10, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[10] Francesco Mercaldo et al., "Experimenting with Extreme Learning Machine for Biomedical Image Classification," *Applied Sciences*, vol. 13, no. 14, pp. 1-20, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Anuradha Chinta et al., "Lumpy Skin Disease Detection in Cows Using Resnet-50," *2023 International Conference on Ambient Intelligence, Knowledge Informatics and Industrial Electronics (AIKIIE)*, Ballari, India, pp. 1-6, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Abdullah Toprak, "Extreme Learning Machine (ELM)-Based Classification of Benign and Malignant Cells in Breast Cancer," *Medical Science Monitor*, vol. 24, pp. 6537-6543, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[13] Shagun Sharma et al., "A Deep Learning Based Convolutional Neural Network Model with VGG16 Feature Extractor for the Detection of Alzheimer Disease Using MRI Scans," *Measurement: Sensors*, vol. 24, pp. 1-8, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Yoleidy Huérfano-Maldonado et al., "A Comprehensive Review of Extreme Learning Machine on Medical Imaging," *Neurocomputing*, vol. 556, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Hao Wei et al., "Extreme Learning Machine-Based Classifier for Fault Diagnosis of Rotating Machinery Using a Residual Network and Continuous Wavelet Transform," *Measurement*, vol. 183, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Wilson Bakasa, and Serestina Viriri, "VGG16 Feature Extractor with Extreme Gradient Boost Classifier for Pancreas Cancer Prediction," *Journal of Imaging*, vol. 9, no. 7, pp. 1-22, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[17] Xianli Liu et al., "Functional Extreme Learning Machine," *Frontiers in Computational Neuroscience*, vol. 17, pp. 1-21, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Harshal Patil, and Kanhaiya Sharma, "Extreme Learning Machine: A Comprehensive Survey of Theories & Algorithms," *2023 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES)*, Greater Noida, India, pp. 749-756, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[19] Musa Genemo et al., "Detecting High-Risk Area for Lumpy Skin Disease in Cattle Using Deep Learning Feature," *Advances in Artificial Intelligence Research*, vol. 3, no. 1, pp. 27-35, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[20] Bezawit Lake, Fekade Getahun, and Fitsum T. Teshome, "Application of Artificial Intelligence Algorithm in Image Processing for Cattle Disease Diagnosis," *Journal of Intelligent Learning Systems and Applications*, vol. 14, no. 4, pp. 71-88, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] M. Rony et al., "Cattle External Disease Classification Using Deep Learning Techniques," *2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, Kharagpur, India, pp. 1-7, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[22] Gaurav Rai et al., "A Deep Learning Approach to Detect Lumpy Skin Disease in Cows," *Computer Networks, Big Data and IoT, Lecture Notes on Data Engineering and Communications Technologies*, pp. 369-377, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[23] Ashwini Pradhan et al., "On the Classification of MR Images Using "ELM-SSA" Coated Hybrid Model," *Mathematics*, vol. 9, no. 17, pp. 1-21, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[24] Suresh Prasad Kannojia, and Gaurav Jaiswal, "Ensemble of Hybrid CNN-ELM Model for Image Classification," *2018 5th International Conference on Signal Processing and Integrated Networks (SPIN)*, Noida, India, pp. 538-541, 2018. [CrossRef] [Google Scholar] [Publisher Link]