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Lumpy Skin Disease Detection Using VGG19 and ANN Hybrid Model

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Abstract

Lumpy Skin Disease (LSD) is a cattle disease caused by a virus and highly contagious and as a result the livestock sector incurs a huge financial loss across the globe. Outbreaks of LSD must be contained and the mortality rate must be kept low, therefore early LSD diagnosis is essential. Traditional diagnosis methods, however, are slow, need a specific type of expertise, and in rural areas the diagnostics are usually out of reach. These factors contribute to a delayed outbreak response and as a result increase the financial strain on the farmers. New disease detection methods that utilize automation and artificial intelligence can provide viable alternatives. In this paper, we present a novel methodology in which we fuse both deep learning and machine learning methods in order to detect LSD accurately. We utilize the VGG19 Convolutional Neural Network (CNN) for the classification of images of cattle with skin disease, and a skin disease detection artificial neural network (ANN) model for disease detection, trained on CSV clinical and environmental features. The disease prediction related image and tabular data used in this study are obtained from Kaggle. The VGG19 model is fine-tuned with the use of transfer learning to develop its feature extraction and classification components. The ANN model has been trained using normalized input features and has been optimized through the use of backpropagation. The amalgamation of these two models increases the stability and reliability of the detection system. Results from experiments show that the VGG19 model demonstrates a record of 92.16% with a loss of 0.2138. On the other hand, the ANN model also shows record of higher accuracy with 96% and the data is said to be structured. In its 0.9215 of the validation accuracy, the VGG19 model shows good performance of ability to generalize. The detection accuracy is further enhanced with the use of the suggested combination of models and this along with its flexibility and simplicity and low cost overall, aids in the early detection of the disease called LSD. With this system in place, it aids in the rapid and effective decision making of the farmers along with the vets and this in turn aids to quell the spread of the disease and improves the overall management of the livestock in the health aspect.

Keywords: *Lumpy Skin Disease, VGG19, Artificial Neural Network, Deep Learning, Image Classification, Disease Prediction.*

1. Introduction

Lumpy Skin Disease (LSD) is a infection in cattle caused by the Capripoxvirus. Symptoms include fever, lumps on the skin, and a drop in the production of milk, and in some instances, the disease is fatal. Farmers and the livestock industry have experienced severe economic impacts because of the rapid spread of the disease in several regions. [1]. When it comes to mitigating disease outbreaks, early detection is critical. However, the conventional methods of disease diagnostics are quite sluggish, and are often reliant on laboratory testing to provide the necessary information, leading to a potential disease outbreak. [2]. Recent advancements in artificial intelligence (AI), and in particular deep learning and machine learning, have paved the way for the creation of disease detection systems that function fully automatically. There is a machine learning technique called convolutional neural networks (CNNs) that has been successful in the detection of a certain type of skin diseases. [3] Other skin diseases have been diagnosed by Structured Data based ML Models [4]. Early disease diagnosis and customized treatment strategies can ultimately be achieved by the prediction of clinical and environmental variables. A number of researchers have utilized deep learning techniques for the identification of diseases. VGG19

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is a transfer learning model that has successfully been utilized in the medical fields to capture a number of images and is one of the more successful models in this regard [5]. Also, it has been demonstrated that multi model hybrid systems are superior to their single model counterpart systems [6]. Although there is great improvement in image classification, reliable accuracy and generalization has proven to be difficult, as noted in several studies, primarily due to variations in images, lighting, and imbalances in an image classification dataset. Relying solely on images for classification may overlook important disease indicators. Therefore, to improve accuracy and comprehension of the disease, a multidimensional, multifaceted approach incorporating clinical data, patient histories and disease images is required. With the advancing clinical data and history disease images, VGG19 (Image Classification) and ANN (structured data) will be used. The goal and benefit of networking to store and manage all created and collected data will be justified with the implementation of the project. Merging the two methodologies will elevate and magnify all classification problems. Therefore, the goal of the project is to detect Lumpy Skin Disease (LSD) as early as possible. The project's purpose is to assist veterinarians and farmers in classifying the disease, thereby minimizing the damage caused by the disease, in order to manage the overall health of the animals and to support the livestock industry.

2. Literature survey

Khotimah et al. [1] developed an ensemble deep learning model for robust identification of Lumpy Skin Disease (LSD) using multiple classifiers. This method achieves a good balance between prediction accuracy and overfitting by using a combination of various deep learning architectures. This study also shows the applicability of ensemble techniques as compared to single models for disease classification. Nevertheless, the model needs a substantial amount of resources for training and deployment, which may discourage use by smaller research teams or budget constrained healthcare facilities. Hussain et al. [2] proposed a framework for LSD detection using an adaptive hybrid optimizer-based approach. This framework combines various optimization methods to adjust model parameters, which improves classification effectiveness. Additionally, the framework optimizes convergence time and accuracy. On the contrary, the advanced optimization techniques come at the cost of elevated computational requirements, which limits the model's ability to operate on large or more intricate datasets. Owada et al. [3] created a geospatial model to examine possible routes for the entry of LSD into Australia. The model incorporates environmental and geographic data to evaluate the potential risks associated with the spread of disease. Their results identify key areas at risk of viral incursions and pinpoint the need for robust surveillance systems to detect and respond to outbreaks of LSD in these zones. Nonetheless, the model prioritizes macro-level forecasting over micro-level disease detection and, as a consequence, the model is not useful for the purposes of real-time outbreak response and targeted health measures. Gouda and Abdallah [4] studied bagging vs. boosting ensemble methods for predicting LSD on multiclass imbalanced datasets. They demonstrate that boosting methods are usually preferred over bagging methods for dealing with class imbalances. This study stresses that choosing the right ensemble methods is crucial when it comes to prediction accuracy. They address the issues that imbalanced datasets present for correctly predicting the presence of a disease, and that it is often very difficult to obtain enough data points for the underrepresented classes, which results in the model performing biasedly. Hossen et al. [5] developed an explicable machine learning framework to detect LSD in the context of climate and environmental factors. The model implements explainable AI methods to ensure prediktions are transparent. This aids stakeholders in understanding the impact of various factors on the occurrence of a disease. Although, the absence of image analysis functionality is a limitation with respect to diagnosis. Maulana et al. [6] proposed an analysis for the spatial risk distribution of LSD in Thailand using a maximum-entropy-based model. The model identifies potential high-risk areas by combining multiple environmental and epidemiological datasets. The model also helps in prioritizing the development of disease prevention and control strategies by illuminating the areas that require the most urgent intervention and the greatest allocation of resources. However, the model's design is more applicable for a long-term regional risk assessment, and therefore, more applicable for less immediate public health responses. This design is a significant detractor for assessing urgent public health responses and where immediate actions are necessary. Olaniyan et al. [7] created a machine learning model for predicting LSD (Lumpy Skin Disease) using some structured datasets. As a result of their work, they achieved a fair amount of accuracy with the use of features from tabular data. Although they had a reasonable success rate without the use of image deep learning, the model has the potential of achieving an even greater success rate by utilizing input of visual data from the skin lesions. Abbas et al. [8] presented an intelligent system for predicting skin illness using transfer learning in combination with explainable AI. The research demonstrated the efficacy of pre-trained CNN models, exemplarily VGG, for tasks of image classification. With the help of their system, accuracy is achieved with consistency in maintaining the ability to explain the reasoning behind the model's decision. This research reinforces the practice of utilizing transfer learning in the analysis of medical images. Gulzar et al. [9] proposed a hybrid approach of deep transfer learning for the prediction of skin disorders. The model integrates numerous deep learning frameworks to facilitate improved feature extraction and classification precision. Their findings exhibit an increase in performance in comparison to individual models. The study attests to the value of hybrid frameworks in performing sophisticated medical diagnosis tasks. Noor et al. [10] examined the use of convolutional neural networks (CNNs) for the diagnosis of skin diseases. Their system combines image-based prediction and a healthcare support system. The study shows that the system is very accurate in detecting different types of skin diseases. This study emphasizes the ability of CNNs to develop automated and scalable systems for clinical diagnosis, and shows that CNNs can help improve the speed and accuracy of skin disease diagnosis in clinical practice.

3. Proposed Methodology

Image / CSV Dataset: With this system, we can work with two different data types: image data, and CSV (or tabular) data. The image dataset consists of cattle skin images that are labeled as being infected and as being healthy. The CSV dataset, on the other hand, consists of images in which the data has been structured in relation to different variables such as temperature, humidity, and health biomarkers. With both of the data types, the model has the capability of defining both visual and numerical patterns, which, in return, would assist in enhancing the system's detection ability overall. Figure 1. [1-5]

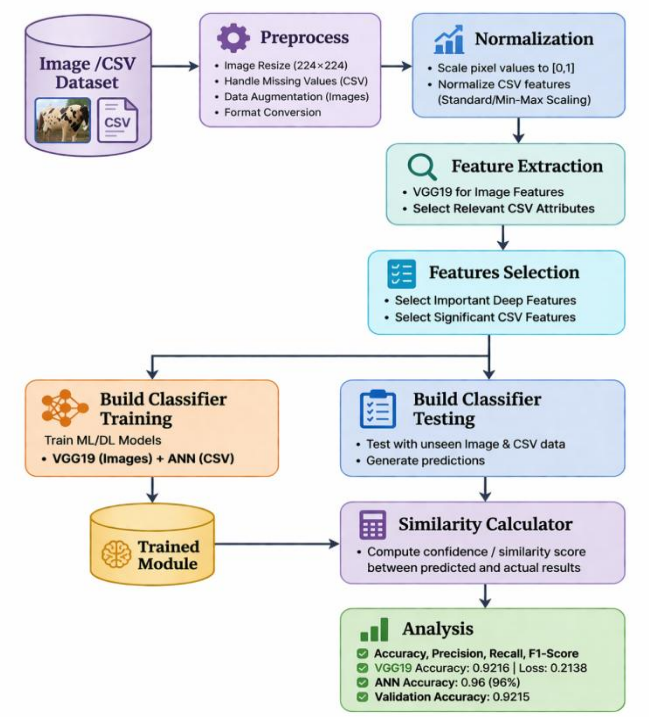

Figure 1 System Architecture of Proposed System List of Modules and Functionality

Preprocessing Model: Preprocessing involves a series of tasks that help in cleaning the raw data. For instance, with image data, the images are resized to a single dimension that would be deemed acceptable by the VGG19 model (224*224) and then data augmentation tasks such as rotation, and flipping are performed on the images to help diversify the dataset. With the CSV data, any missing data values must be dealt with and any categorical variables must be converted to numerical equivalents (this is called data encoding). It is these tasks that help to develop data that is consistent, and is of high enough quality to be utilized as inputs for the model. [6-10]

Normalization: With regards to the model's performance, it can be enhanced in relation to the bettering of the performance of the model by scaling the inputs to a single value. For images datasets, the pixel values of the images are commonly scaled to between 0 and 1. While for CSV datasets, the values in the dataset may be scaled using either the min-max scaling method, or via the standardization method (these are the methods that normalize the data). The normalization of data causes the model to be able to converge more quickly in relation to the model's training and therefore assists in preventing the model from focusing more on the features that are in relation to the higher values as opposed to the other features that have lower values. [11-15]

Feature Extraction: Pattern recognition helps engender feature extraction. For example, on the VGG19 model, deep features like shapes and textures are automatically extracted. For CSV data, the extraction is done by selecting attributes based on relevancy. Doing this reduces the data and extracts the meaningful information. This is central to increasing prediction accuracy.

Feature Selection: Only the most applicable attributes are selected during feature selection, which refines the dataset even further. This selection process is responsible for getting rid of attributes that are redundant and irrelevant, and this ultimately ends up being positively impactful on the performance of the model. Selection during this step decreases the complexity and cost associated with the model, and increases its ability to generalize. This results in better accuracy and efficiency of the entire system.

Build Classifier – Training

In this phase, the data that has already been prepared is used to train both models. VGG19 has to classify and train images with deep learning by means of transfer learning. The CSV data is used to teach the ANN model to learn the relationships existing between the features and the outcomes of the disease. The two models learn their data sets and patterns in isolation. Training them in this manner and simultaneously is what facilitates the system's high robustness. Once the training process has commenced, the Trained Modules are saved. The saved modules embody the weights and adjustable contractile parameters that were learned throughout training. The trained models may be reused for future predictive modeling, thereby saving time and effort even in the initial stage of implementation, as the models are pre-trained through storage and can even be used in immediate detection of disease.

Build Classifier – Testing: Evaluation of performance by testing trained models is done through unseen data. The trained models are designed to associate the input data with the presence or absence of a disease, and this is a means through which one can evaluate the models' capability of generalization within unseen data. Testing is done separately for images and for any inputs in CSV format and these results will assist in the evaluation.

Similarity Calculator: The predicted results and the actual outcomes will be compared by the Similitude Calculator. There is a confidence score or a prediction level that is identified by the calculator, and this is one of the predictive outcomes that are closest to the actual outcomes, so this aids in testing the reliability of a given model, and this will assist in advanced testing of model performance.

Analysis

The maximum performance of the design system will be evaluated during this final stage. The precision, recall, F1 score and accuracy will be evaluated. The ANN model has a higher accuracy compared to the VGG19 model which has 92.16% accuracy and a loss of 0.2138, as the ANN model has 96% accuracy. The numbers also portray a positive application of the Hybrid Model.

Algorithm 1: VGG19 for Lumpy Skin Disease Detection

Input: Image Dataset D_img

Output: Predicted Class (LSD / Normal)

Step 1: Load image dataset D_img

Step 2: For each image in D_img do

Resize image to 224 × 224

Normalize pixel values to [0,1]

Apply data augmentation (flip, rotation)

End For

Step 3: Split dataset into training set (Train_img) and testing set (Test_img)

Step 4: Load pretrained VGG19 model with ImageNet weights

Remove top layers of VGG19

Add new layers:

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Flatten layer
Dense layer with ReLU activation
Dropout layer
Output layer with Softmax activation
Step 5: Compile model using:
Optimizer = Adam
Loss = Categorical Cross entropy
Metrics = Accuracy
Step 6: Train model using Train_img for N epochs
Validate model using Test_img
Compute accuracy and loss
For each test image do
Predict class label (LSD / Normal)
End For
Step 7: End

Algorithm 2: ANN for Lumpy Skin Disease Prediction
Input: CSV Dataset D_csv
Output: Predicted Class (LSD Risk / Normal)
Step 1: Load CSV dataset D_csv
Step 2: Handle missing values in D_csv
Encode categorical features
Normalize numerical features using Min-Max scaling
Step 3: Perform feature selection to remove irrelevant attributes
Step 4: Split dataset into training set (Train_csv) and testing set (Test_csv)
Step 5: Initialize ANN model:
Input layer with n features
One or more hidden layers with ReLU activation
Output layer with Sigmoid/Softmax activation
Step 6: Compile model using:
Optimizer = Adam
Loss = Binary/Categorical Cross entropy
Metrics = Accuracy
Step 7: Train ANN model using Train_csv
Step 8: Evaluate model using Test_csv
For each test instance do
Predict class label (LSD Risk / Normal)
End For
Step 9: End

4. Results and Discussion

The evaluation of both VGG19 (a subtype of deep learning) and ANN (artificial neural networks) models showcases the advantages of both deep learning and machine learning techniques. The VGG19 model performs very well in image classification and is able to extract the relevant features of the images of the cattle skins very well. The only issue with the model was the validation loss. The model was very slightly sensitive to the variance in the datasets. The ANN model on the other hand behaved more consistently and more stably because of the structure of the CSV data (which is more likely to be the reason why the data has more order). On the Training/Validation accuracy curves, the lines of each are extremely close to each other, the lines of each (both the Training and Validation) drop, and the number of over fitting is minimal. The ANN model was stable and because of this gained higher accuracy (96%) as compared to VGG19. The analyses are proof that ANN is better in analyzing data in a structured form, while VGG19 is better in analyzing and extracting data in visual form. Thus, the combination of ANN and VGG19 models in a hybrid model is able to increase the accuracy of the system and also the effectiveness of the system by using both techniques in order to digitally monitor the lumpy skin disease. Figure 2.

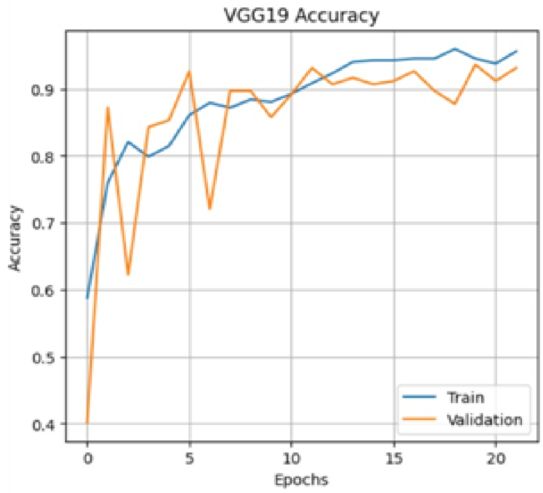

Figure 2 VGG19 Accuracy

The performance of model VGG19 is illustrated in Figure 2 focused on accuracy and loss metrics in different epochs. The accuracy chart shows the training accuracy consistently growing from roughly 0.58 to over 0.94, so the model is learning the features

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of the images over the epochs. The training and validation accuracies share this upward trajectory, however, training accuracy remains more stable while validation accuracy sees more fluctuation. This is typically the case in deep learning, and is largely due to the validation set and the model still appearing to be sensitive to the features of the validation set like the images and/or noise as this causes models to perform poorly on data that is not represented in the training set. Figure 3.

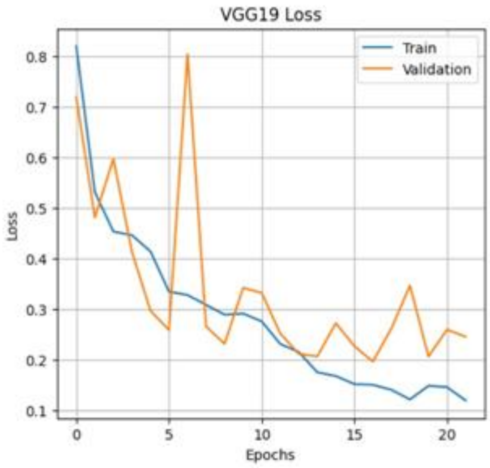

Figure 3 VGG19 Loss

The loss graph in Figure 3 shows consistent reduction in training loss, from about 0.82 to below 0.15, which shows better model convergence. Validation loss also shows an overall decrease, despite some occasional spikes. This minor over fitting and/or sensitivity to validation samples. The training-validation curves showed a less than small gap, which shows better generalization capability. Figure 4.

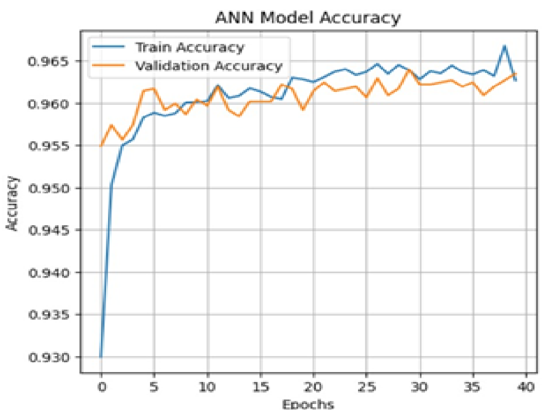

Figure 4 ANN Model Accuracy

The performance of the ANN model, using structured CSV data, is presented in Figure 4. Accuracy and loss graphs were used to assess performance. The accuracy graph shows a steep increase, closing at around 0.96 with some fluctuations. The training and validation accuracy graphs are almost identical, so we conclude that consistent learning took place, and that overfitting occurred a little. Figure 5.

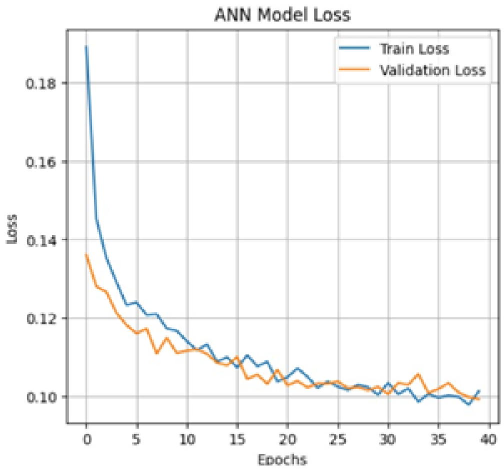

Figure 5 ANN Model Loss

Loss figure 5 depicts a gradual drop in both training and validation loss, ranging from 0.19 to approximately 0.10. This gradual and continuous drop in loss shows efficient optimization and effective learning of the relationships of the underlying features. Unlike the VGG19 model, the ANN model shows more consistent validation behavior, which can be linked to the organized format of the CSV data. This organization helps the model better process the input features, which in turn reduces overfitting during training. [15-20]

Conclusions

In this research, we develop a novel hybrid artificial intelligence system, incorporating both imaging and structured data, for the identification of Lumpy Skin Disease (LSD). The system combines a VGG19 deep learning model and an artificial neural network (ANN). This model combination has proven superior in detection accuracy and reliability than ANN detection based on a single model. The VGG19 deep learning model has a successful record in recognizing visual diseases in cattle and reached an accuracy of 92.16%. The ANN, on the other hand, processes structured data in CSV format and demonstrated an accuracy of 96%. Hence, the ANN is efficient with the data pertaining to an environment and clinical phenomena. The hybrid nature of the system results in improved performance through the use of both models. It helps in early and accurate detection of the disease as the system operates at the first, last, and/or only frontier of the region. Access to veterinary professionals is a frequent setback in the management of livestock health, and this system addresses that by providing the livestock healthcare workers with a highly efficient tool. The system has a high potential to assist in the alleviation of the negative economic impact as well as the spread of Lumpy Skin Disease by providing real-time monitoring (via mobile apps or IoT based systems). The proposed systems are scalar, less expensive than systems providing similar services.

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