Enhanced Detection in Lumpy Skin Disease using Depth-wise Separable Structure through Deep Learning

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Abstract - A viral illness, lumpy skin in cattle is spread by mosquitoes and other insects that feed on human blood. Animals that have never been exposed to the virus are mostly affected by the sickness. Milk, meat, and domestic and international livestock commerce are all impacted by cattle lumpy skin disease. Traditional lumpy skin disease diagnosis is exceedingly time-consuming, complicated, and resource-constrained. As a consequence, it is essential to use deep learning algorithms that can categorize the condition with excellent performance outcomes. In order to segment and classify diseases using deep features, deep learning-based segmentation and classification are suggested. Convolutional neural networks with 10 layers have been selected for this. The created framework is first trained using data gathered from cattle with Cattle's Lumpy Skin Disease (CLSD). The skin tone is crucial to identifying the damaged region when a disease is represented since the characteristics are derived from the input photographs. To do this, a color histogram was utilized. A deep pre-trained CNN uses this divided region of altered skin color to extract features. Next, a threshold is used to transform the produced result into a binary format. The classifier for classification is MobileNetV2 Transfer Learning. The suggested methodology's classification performance has a 96% CLSD accuracy rate. We give a comparison with cutting-edge methodologies to demonstrate the efficacy of the suggested strategies.

Keywords: CLSD, CNN, MobileNetV2, Deep Learning, Transfer Learning.

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I. INTRODUCTION

Skin diseases are a broad range of conditions affecting the skin, and include diseases caused by bacterial infections, viral infections, fungal infections, allergic reactions, skin cancers, and parasites. Skin infections are conditions affecting the skin. These are diseases that can cause inflammation, itchiness, rashes, and other skin changes. Certain skin conditions are genetic, while there are others caused due to lifestyle factors. Treatment for different skin conditions includes ointments, creams, medications, and lifestyle changes. The skin is a large organ covering and protecting the human body.

It serves varied functions like:

- Holding in fluid and preventing dehydration
- Keeping out viruses, bacteria, and other causes of diseases
- Helping you feel different sensations, like pain or temperature
- Synthesizing vitamin D
- Stabilizing body temperature Issues of the skin include all those conditions that inflame, clog, and

irritate the skin causing rashes, and other changes in the skin appearance.

Skin diseases contribute to 1.79% of the universal burden of diseases across the world. According to the American Academy of Dermatology Association. 1 in 4 individuals in the US has skin issues. Skin diseases can greatly vary in severity and symptoms, and they can be permanent or temporary, painful or painless. Some skin infections can be minor, while others can be life-threatening.

II. LITERATURE REVIEW

Musa sativa L. et. Beetles and other bloodsucking insects like mosquitoes spread the virus that causes Cattle's lumpy skin disease [1]. Infected animals are often those that have never been exposed to the virus before. Milk, meat, and the worldwide and domestic livestock commerce are all affected by the cattle lumpy skin disease. It takes a lot of time, money, and expertise to properly diagnose a bump on the skin using conventional methods. This makes it essential to use deep learning algorithms capable of illness classification with high accuracy. Because of this, we suggest employing deep features in conjunction with deep learning for illness segmentation and classification. Convolutional neural networks with 10 layers were used for this purpose. To begin, the created framework is trained using data gathered on Cattle's lumpy skin disease (CLSD). Since the color of the skin is crucial for identifying the afflicted region in the course of disease representation, we employed a color histogram to extract the characteristics from the input photos. A deep, pre-trained CNN is then utilized to extract features from the segmented region of impacted skin color. Next, a threshold is applied to the output to turn it into a binary. Classification is performed using the Extreme learning machine (ELM) classifier. We give a comparison with state-of-the-art approaches to demonstrate the efficacy of the suggested methods and show that their classification performance attained an accuracy of 0.9012% on CLSD.

As per al [2], LSD is a significant transboundary sickness that significantly affects the worldwide steers business. The scientists set off to gauge future LSD scourge reports all through Africa, Europe, and Asia, as well as distinguish designs and basic defining moments. Information from the World Association for Creature Wellbeing's LSD pandemic reports (January 2005 to January 2022) were assessed. By using paired division, we recognized measurably huge advances in the information and utilized ARIMA and NNAR models to foresee the future number of LSD reports. Every mainland has four significant temporary areas pinpointed. The middle number of LSD reports was most prominent in the African information during the third and fourth change focuses (2016-2019). Enormous scope LSD pandemics in Europe all crested somewhere in the range of 2015 and 2017. After the third noticed shift in 2018, Asia kept on driving the world in 2019 LSD reports. Both the ARIMA and NNAR models project an expansion in LSD reports in Africa during the following three years (2022-2024), while extending a steady number of reports in Europe. While NNAR expects an ascent in Asian flare-ups in 2023 and 2024, ARIMA anticipates a consistent number of such events. The consequences of this exploration assist specialists with diving more deeply into the spread of LSD all over the planet.

Azeem et al. As of late, the infection that causes knotty skin has spread to non-endemic locales, like the Center East and Asia, as verified by al [3]. Ongoing reports of LSD episodes in Asian countries including Bangladesh, India, China, Nepal, Bhutan, Vietnam, Myanmar, Sri Lanka, Thailand, Malaysia, and Laos are justification for extensive concern for the steers and dairy areas there. This study gives a succinct outline of the new LSD pestilences in southern Asia and features the peril they address to nearby countries. A few measures and strategies are proposed to check the spread of this new sickness in Asia. In case it wasn't already obvious, I'm Punyapornwithaya et. Various instances of knotty skin sickness (LSD) spread to Thai cow ranches in 2021 and 2022, as announced by al [4]. The country has until recently never seen a LSD pandemic before this one. Thus, there is a requirement for additional exploration on the study of disease transmission of LSD. The reason for this examination was to look at the worldly and spatial elements of LSD scourges in dairy-creating areas. Utilizing spatio-worldly models, for example, space-time stage, Poisson, and Bernoulli models, we examined information from LSD flare-up examinations acquired from dairy ranches in Khon Kean area, northern Thailand. From May through July of 2021, LSD was found on 133 out of 152 dairy ranches. The June LSD flare-ups influenced an enormous number of dairy ranches (n = 102). Group assault, sickness, and passing rates were separately 0.87%, 31%, and 0.9% generally. The most likely, not entirely settled by the discoveries, everything being equal, were situated in the northern part of the examination locale. 15 and 6 spatio-worldly flare-up groups were figured out utilizing the space-opportunity stage and Poisson models, individually, while only one bunch was found utilizing the Bernoulli model. These models foresee bunches with radii of 1.59, 4.51, and 4.44 kilometers. Both the space-time change model and the Poisson model found a similar pandemic locale, since all homesteads remembered for the bunch were likewise remembered for the group viewed as by the other model. It was likewise finished up from the exploration that ranchers who lived inside a kilometer of the LSD pestilence site ought to be encouraged to take more grounded bug vector control endeavors. The spatial and transient construction of LSD groups at the focal point is better grasped thanks to this work. This exploration might assist specialists with focusing on high-risk areas for asset designation and better get ready for future pestilences. "Mishra et. Foot-and-mouth sickness plagues have caused critical monetary misfortunes in various countries, including Thailand, as verified by al [5].

Specialists' capacity to execute a FMD checking and control program is worked with by guaging, a fundamental early admonition apparatus. Time-series strategies like occasional autoregressive coordinated moving normal (SARIMA), blunder pattern irregularity (ETS), brain network autoregression (NNAR), Geometrical Dramatic smoothing state-space model with Box-Cox change, ARMA mistakes, Pattern and Occasional parts (TBATS), and cross breed techniques were utilized to show and foresee the month-to-month number of FMD flare-up episodes (n-FMD episodes) in Thailand. From January 2010 through December 2020, a sum of 1,209 month to month events of n-FMD were broke down utilizing these strategies. The quantity of n-FMD occasions hoped to develop somewhere in the range of 2014 and 2020, but the general pattern from 2010 to 2020 was consistent. Every year, the level of the pandemic season was between the long stretches of September and November. The most dependable time series models were made utilizing single-technique draws near.

III. PROBLEM IDENTIFICATION

Following are the problem identification on the basis of existing work:

1. Some of the major issues in the LSDP are security and class imbalance. Class Imbalance can greatly reduce the accuracy of classifiers as False negative are increased. Hence, validation accuracy of train data may decrease. There is a need to effectively handle class imbalance [1].
2. Accurate classification is most important for protect from skin disease. Implementing prediction model with ML algorithms have become necessary for improve accuracy [1, 2].

4. RESEARCH OBJECTIVES

So, following are the objectives of the proposed work:

1. To increase predictive performance of LSDP models using Machine Learning with feature extraction through PCA for handling class imbalance in real world datasets in terms of classification metrics, such as accuracy, F1-score, etc.

2. To perform prediction using machine learning with PCA using specific kernel function while maintaining the accuracy of classifiers.

3. To evaluate and validate the results of proposed method against existing work.

5. METHODOLOGY

The algorithm is as follows

Step 1: Load image from specified path.

Step 2: Feature transform of image data.

Step 3: Partition data into train and test data. Validate the feature data.

Step 4: Apply MobileNetV2 Model.

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Step 5: Train model with test data. Step 6: Evaluate Accuracy.

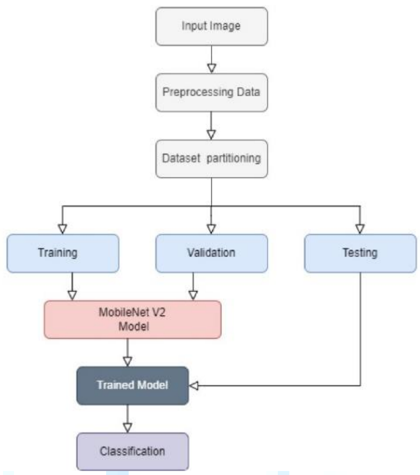

Figure 1: Architecture of Proposed Model

6. RESULTS AND ANALYSIS

The implementation was done using Python 3.11.1 and Jupyter Notebook. You may use Jupiter Notebook, an open-source application that combines data preparation, implementation of several machine learning algorithms, and visualization tools, to design and utilize machine learning techniques. Using Jupyter Notebook, an open-source, web-based interactive environment, you can create and share documents containing live code, mathematical equations, photos, maps, charts, visualizations, and narrative prose. It supports a large number of different languages, including Python, PHP, R, C#, and others. The hardware's technical specifications are as follows: 8 GB of RAM and 512 GB of ROM on an Intel i5 10th generation machine operating at 1.19 GHz. In the public LSD dataset, people with lumpy skin make up 60% of the total photos, whereas those with smooth skin make up 70%. We use 325 photographs of the data to train the model, and 700 images to test it. The major emphasis of this data collection is skin disorders.

Any LSD system and machine learning approach must start with the data sets. The data sets are essential for assessing and verifying the effectiveness of the LSD system. The datasets are often divided into two parts: a training segment and a testing section. The test set is utilized as input into the model to carry out various tasks, whereas the training set is the actual data set used to train the model.

The LSD data collection is the one that provides the most comprehensive analysis of the lumpy skin disorders. Both the test and train data sets include a respectable number of records, which facilitates evaluation and eliminates the need to pick out certain data from it. There are 1025 photos in the collection. Table 1 in the dataset provides two distinct skin types: Lumpy Skin and Normal Skin.

Table 1: Dataset Classes

Class	Images
Lumpy Skin	
Normal Skin	

The performance measures listed below are used to assess the effectiveness of various machine learning-based IDS (Gao, et al., 2019).

• True Positive (TP) - If an attack is truly being launched after being identified. Therefore, a genuine positive is only a reliable assault detection.

• False Positive (FP) - When an attack is detected but it is not really an attack. A false positive is thus only a false warning.

• True Negative (TN) - Data that is appropriately classified as normal and is normal. Therefore, a successful identification of a normal piece of data is the genuine negative.

Attack data that has been incorrectly classified as normal is known as a false negative (FN). The most hazardous situation is one where no one knows about the assault that has already occurred.

• The ratio of the total number of observations to the sum of the genuine positive and negative values is known as accuracy. In other words, the accuracy typically determines the overall number of classifications that are accurate. An important performance criterion for assessing the classifier is accuracy. In equation 1, the accuracy formula is described.

Accuracy is calculated as (TP+TN) / (TP+TN+FP+FN) …. (1).

According to equation 2, precision is defined as the ratio of true positive observations to the total of both true and false positive observations.

Precision is equal to TP / (TP+FP) (2).

• The recall (Sensitivity) determines how many correct classifications are punished by how many items are missing. Equation 3 discusses the recall formula.

Recall (Sensitivity) is equal to TP / (TP+FN) (3).

• The percentage of true negatives that the model properly detects is known as specificity. This suggests that a further percentage of true negatives—which were once thought to be positive and may be referred to as false positives—will be reported. A True Negative Rate (TNR) might also be used to describe this percentage.

TNR (Specificity) is calculated as TN / (TN + FP) (4).

Following the pre-processing of the data in this experiment, the top ten features of the dataset are chosen using the features selection technique, and then well-known supervised and unsupervised learning methods are put into practice. Support Vector Machine (SVM), XGBoost, and Extreme Learning Machine (ELM) are used in machine learning. The suggested MobileNetV2 model belongs to the Efficient CNN subcategory.

Figure 2: Instances in Dataset

Table 2: Experiment Results of Machine Learning Models

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

Table 2 displays the experiment results for various machine learning methods, whereas Table 2 displays the experiment results for various machine learning algorithms, including the suggested model. The comparison between the suggested model and the state-of-the-art model is shown in Table 3.

Table 3: Experiment Results of Different Machine Learning Algorithms including the Proposed Model

Method	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
ESD	89.00	89.89	90.00	89.80
M-SVM	89.00	89.00	90	89.11
XGBoost	90.01	89.00	89.25	89.92
ELM	90.01	90.05	90.19	90.06

Proposed	91.31	90.84	92.14	94.11

In this part, we compare the outcomes produced by our suggested simulation model to those produced by earlier suggested models. Table 4.3 displays our findings and contrasts them with findings from other models.

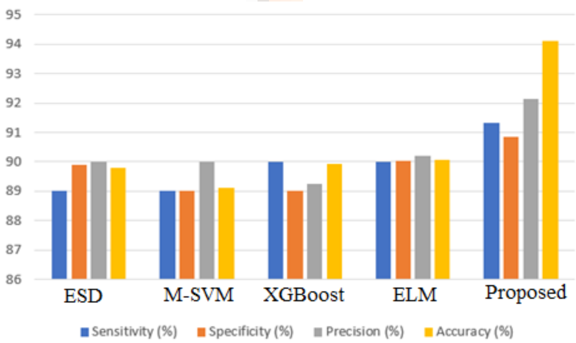

Figure 3: Performance Analysis of Different Models

7. CONCLUSIONS

This study offered a segmentation and classification model for the lumpy skin condition of cattle. A transfer learning approach using MobiltNetV2 was detailed in the framework. On the well-known datasets for the lumpy skin disease in cattle, the suggested technique was assessed. Different kinds of supervised and unsupervised learning approaches are analyzed using F1-Measure, recall, precision, and recall, which are briefly addressed. The Fisher score approach was used to examine and pre-process the LSD after it was obtained from the Kaggle library. This method minimizes the number of features in the dataset and prevents the over-fitting issue. On the pre-processed dataset, supervised and unsupervised machine learning methods are used. The ensemble model outperforms all other models including the state-of-the-art model when the performance of all the methods is compared.

The following are the thesis's future focuses:

• To provide a thorough analysis of Deep Learning algorithms using a real-time dataset to offer a better solution for the intrusion detection system.

• Looking at novel pre-processing methods that might increase model accuracy.

• The performance of the LSD detection system may be improved by using deep learning methods.

REFERENCES

[1] Musa Genemo, “Detecting high-risk Area for Lumpy Skin Disease in Cattle Using Deep Learning Feature”, Advances in Artificial Intelligence Research (AAIR), Vol. 3 (No. 1), pp. 27-35, ISSN 2757-7422, (2023).

[2] Ayesha Anwar, Kannika Na-Lampang, Narin and Veerasak, “Lumpy Skin Disease Outbreaks in Africa, Europe, and Asia (2005–2022): Multiple Change Point Analysis and Time Series Forecast”, MDPI Journal, (2022).

[3] Azeem, S.; Sharma, B.; Shabir, S.; Akbar, H.; Venter, E., “Lumpy skin disease is expanding its geographic range: A challenge for Asian livestock management and food security”. Vet. J. (2022), 279, 105785.

[4] Punyapornwithaya, V.; Seesupa, S.; Phuykhamsingha, S.; Arjkumpa, O.; Sansamur, C.; Jarassaeng, C. Spatio-temporal patterns of lumpy skin disease outbreaks in dairy farms in northeastern Thailand. Front. Vet. Sci. (2022), 9, 957306.

[5] Punyapornwithaya, V.; Mishra, P.; Sansamur, C.; Pfeiffer, D.; Arjkumpa, O.; Prakotcheo, R.; Damrongwatanapokin, T.; Jam-pachaisri, K. Time-Series Analysis for the Number of Foot and Mouth Disease Outbreak Episodes in Cattle Farms in Thailand Using Data from 2010–2020. Viruses (2022), 14, 1367.

[6] Perone, G. Comparison of ARIMA, ETS, NNAR, TBATS and hybrid models to forecast the second wave of COVID-19 hospitalizations in Italy. Eur. J. Health Econ. (2022), 23, 917–940.

[7] Maw, M.T.; Khin, M.M.; Hadrill, D.; Meki, I.K.; Settypalli, T.B.K.; Kyin, M.M.; Myint, W.W.; Thein, W.Z.; Aye, O.; Palamara, E. First Report of Lumpy Skin Disease in Myanmar and Molecular Analysis of the Field Virus Isolates. Microorganisms (2022), 10, 897.

ISSN: 2582-8150

[8] Singhla, T.; Boonsri, K.; Kreausukon, K.; Modethed, W.; Pringproa, K.; Sthitmatee, N.; Punyapornwithaya, V.; Vinitchaikul, P. Molecular Characterization and Phylogenetic Analysis of Lumpy Skin Disease Virus Collected from Outbreaks in Northern Thailand in (2021). Vet. Sci. 2022, 9, 194.

[9] Khalil, M.I.; Sarker, M.F.R.; Hasib, F.Y.; Chowdhury, S. Outbreak investigation of lumpy skin disease in dairy farms at Barishal, Bangladesh. Turk. J. Agric. Food Sci. Technol. (2021), 9, 205–209.

[10] Lu, G.; Xie, J.; Luo, J.; Shao, R.; Jia, K.; Li, S. Lumpy skin disease outbreaks in China, since 3 August 2019. Transbound. Emerg. Dis. (2021), 68, 216–219.

[11] Chibssa, T.R.; Sombo, M.; Lichoti, J.K.; Adam, T.I.B.; Liu, Y.; Elraouf, Y.A.; Grabherr, R.; Settypalli, T.B.K.; Berguido, F.J.; Loitsch, A. Molecular analysis of East African lumpy skin disease viruses reveals a mixed isolate with features of both vaccine and field isolates. Microorganisms (2021), 9, 1142.

[12] Fatemeh Namazi and Azizollah Khodakaram Tafti, "Lumpy skin disease, an emerging transboundary viral disease: A review", Vet Med Sci. (2021) May; 7(3): 888–896.