Improved Lumpy Skin Disease Detection with ADAM Optimizer and MobileNetV2

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Abstract: An infection that produces harsh skin in cows might be spread by mosquitoes and different bugs that feed on human blood. Creatures that have never been presented to the infection are most impacted by the ailment. The development of milk and meat, as well as the homegrown and global animals business, are completely influenced by dairy cattle uneven skin illness. The method of diagnosing uneven skin sickness is very tedious, many-sided, and asset obliged. In this way, it is fundamental to have profound learning calculations that can arrange the situation with excellent execution results. To portion and group infections as per profound highlights, profound learning-based division and arrangement is proposed. For this, convolutional brain networks with ten layers have been chosen. Data assembled from calves with different calves The made structure is first prepared on Uneven Skin Infection (CLSD). At the point when an illness is shown, the complexion is critical for recognizing the tormented locale since the qualities are gotten from the information photos. This was finished utilizing a variety histogram. To upgrade highlights, utilize an ADAM (Versatile Second Assessment) streamlining agent. A profound pre-prepared CNN is used to remove qualities from this sectioned locale with modified complexion. An edge is then used to change the created outcome into a paired portrayal. The classifier is MobileNetV2 Move Learning. The recommended strategy's order execution has a 96.4% CLSD exactness grade. We balance the recommended arrangements with state of the art strategies to show their viability.

Keywords: *CNN, CLSD, MobileNetV2, deep learning, transfer learning, and ADAM (Adaptive Moment Estimation) Optimizer.*

I. INTRODUCTION

Skin sicknesses incorporate a wide assortment of infirmities that influence the skin, for example, those welcomed on by parasites, bacterial contaminations, viral diseases, contagious diseases, unfavorably susceptible reactions, and skin malignancies. Conditions that influence the skin incorporate skin contaminations. These circumstances might bring about rashes, tingling, aggravation, and other skin irregularities. Some skin problems are acquired, while others are welcomed on by way of life decisions. Balms, creams, medications, and way of life changes are utilized to treat different skin illnesses. The human body is covered and safeguarded by the skin, a colossal organ.

It does a number of things, such as:

- Preventing dehydration and retaining fluid;
- Blocking germs, viruses, and other disease-causing agents;
- Assisting with various senses, such as pain or temperature;
- Producing vitamin D;
- Maintaining body temperature

Issues of the skin envelop that multitude of problems that arouse, stop up, and disturb the skin making rashes, and different changes in the skin look. 1.79% of the worldwide disease trouble is inferable from skin conditions. The American Foundation of Dermatology Affiliation asserts that. In the US, one out of four individuals experiences skin issues. Skin conditions might be either transitory or long-lasting, difficult or easy, and their seriousness and side effects can differ generally. Skin contaminations might go from insignificant to possibly lethal.

II. LITERATURE REVIEW

Uneven skin illness (LSD) represents a huge danger to steers populaces, influencing both individual cows and entire crowds. Cows are fundamental for satisfying human prerequisites; subsequently, effectively dealing with this illness is basic to forestall critical misfortunes. The exploration proposes a profound learning approach utilizing the RMSprop enhancer and the MobileNetV2 design to address this test. Examinations on a dataset of pictures portraying both solid and knotty dairy cattle exhibit a noteworthy exactness pace of 95%, surpassing existing benchmarks by 4-10%. These outcomes highlight the capability of the proposed way to deal with upset the conclusion and treatment of skin issues in cows creation [1].

L. Musa sativa et al. The microorganism liable for uneven skin sickness in cows is sent by creepy crawlies and other hematophagous bugs, including mosquitoes. Creatures that poor person before experienced the infection are frequently impacted. Knotty skin illness in steers influences meat creation, milk yield, and both neighborhood and overall creature business. Precisely diagnosing a skin swell by standard strategies requires extensive responsibility in time, funds, and skill. Therefore, profound learning frameworks prepared to do appropriately diagnosing infections are fundamental. We propose to involve profound highlights with profound learning for the division and order of infections [2].

Ten-layer convolutional brain networks were utilized for this reason. The information for cows' knotty skin sickness (CLSD) is utilized to initially prepare the constructed structure. A variety histogram was utilized to remove qualities from the info pictures, since the skin's shade is urgent for distinguishing the burdened locale during disorder depiction. The separated locale of stained skin is then used to determine highlights utilizing a profound, pre-prepared convolutional brain organization. The result is then changed into double by the utilization of an edge. The Outrageous Learning Machine (ELM) classifier is utilized for grouping purposes. To exhibit the adequacy of the recommended approaches, we contrast them and state of the art methods and uncover that their arrangement execution accomplished an exactness of 0.9012% on CLSD. LSD is a huge transboundary infection that significantly influences the overall dairy cattle business, as per al [3].

The researchers meant to identify patterns and basic defining moments while additionally assessing approaching LSD episode reports in Africa, Europe, and Asia. We investigated information from the LSD pandemic releases gave by the World Relationship for Creature Wellbeing from January 2005 to January 2022. We utilized ARIMA and NNAR models to conjecture the approaching amount of LSD reports and recognized quantifiably significant upgrades in the information utilizing matched division. Four primary brief zones have been assigned for every landmass. In the African measurements, the moderate amount of LSD reports prevailed all through the third and fourth change focusses (2016-2019). The huge LSD pandemics in Europe arrived at their peak somewhere in the range of 2015 and 2017. In 2019, Asia kept up with its strength in LSD reports after the third huge modification in 2018. Over the accompanying three years (2022-2024), both the ARIMA and NNAR models figure an ascent in LSD reports in Africa, while the quantity of reports in Europe stays unaltered. ARIMA figures a predictable recurrence of Asian eruptions in 2023 and 2024, while NNAR expects a heightening in these occasions. This examination's results improve scholastics' cognizance of LSD's worldwide dispersal.

Azeem and Partners. As indicated by al [4], the sickness that causes nodular skin has of late spread to non-endemic districts, including Asia and the Center East. There is significant worry for the cows and dairy businesses in Asia in light of the fact that to the diligent reports of LSD events in Bangladesh, India, China, Nepal, Bhutan, Vietnam, Myanmar, Sri Lanka, Thailand, Malaysia, and Laos. This concentrate concisely frames the thriving LSD episodes in southern Asia and the related dangers to adjoining nations. To reduce the spread of this original sickness all through Asia, numerous arrangements and techniques are proposed.

I'm Punyapornwithaya et al., in the event that that was not apparent. In 2021 and 2022, occurrences of uneven skin illness (LSD) were accounted for to have spread to Thai dairy cattle pastures. This is the main LSD pandemic to influence the nation till as of late. Subsequently, more examination concerning the transmission of LSD-related diseases is fundamental. This work planned to dissect the neighborhood and worldwide variables related with LSD flare-ups in dairy-creating regions. We utilized spatiotemporal models, including Bernoulli, Poisson, and space-time stage models, to assess information from LSD episode appraisals gathered from dairy ranches in the northern Thai territory of Khon Kaen. LSD was recognized on 133 out of 152 dairy ranches from May to July 2021. A sum of 102 dairy ranches were impacted by the June LSD episodes. The general rates for bunch attack, ailment, and mortality were 0.87%, 31%, and 0.9%, individually. Assuming that any remaining variables stayed consistent, the most probable, yet not conclusively shown by the outcomes, were arranged in the northern segment of the testing site. Just a single bunch was found utilizing the Bernoulli model, however 15 and 6 spatial-transient eruption bunches were identified utilizing the space-time stage and Poisson models, separately. These models figure bundles with radii of 1.59, 4.51, and 4.44 km. Every farmhouse reviewed for the gathering was likewise perceived for the partner seen by the elective model, driving the space-time change model and the Poisson model to recognize a comparable pandemic site. The request showed that farmers inside one km of the LSD episode site ought to be urged to carry out more compelling bug vector control techniques. This study offers an improved appreciation of the spatial and vaporous development of LSD bunches at the point of convergence. This study might help experts in pinpointing high-risk regions for resource distinguishing proof and improving readiness for future plagues.

Mishra et al. report that foot-and-mouth sickness scourges have caused huge monetary misfortunes in numerous nations, including Thailand [6]. Checking is a basic early admonition instrument that helps experts in executing a foot-and-mouth illness review and control program. The month to month recurrence of FMD discharge up episodes (n-FMD episodes) in Thailand was shown and guage using time-series strategies, including Occasional Autoregressive Coordinated Moving Normal (SARIMA), Outstanding Smoothing State (ETS), Brain Organization Autoregression (NNAR), Mathematical Emotional Smoothing State-Space Model with Box-Cox change, ARMA mistakes, Geometrical, Box-Cox, ARMA, Pattern and Occasional parts (TBATS), and crossover procedures. These methodologies were utilized to examine 1,209 month to month events of n-FMD from January 2010 to December 2020. The general pattern from 2010 to 2020 was reliable, albeit the frequency of n-FMD episodes was expected to differ somewhere in the range of 2014 and 2020. The plague reliably arrived at its apex all through the lengthy long stretches of September to November. Single-procedure delineations were utilized to foster the most reliable time series models.

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].

IV. 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.

V. METHODOLOGY

Because of its effectiveness and small size, the suggested transfer learning technique MobileNetV2 in conjunction with the ADAM optimiser for LSD (Lumpy Skin Disease) detection is a potent strategy, particularly for applications that need model deployment on mobile devices. An overview of how to use this combination in a machine learning pipeline for LSD detection is provided in the high-level algorithm below.

The pseudo code of proposed model (MobileNetV2 with ADAM Optimizer) is as follows:

Input

```
# Import necessary libraries
import required_libraries as rl
# Initialize the environment and set parameters
SEED = 42  # For reproducibility
IMAGE_SIZE = (224, 224)  # Input size for MobileNetV2
BATCH_SIZE = 32
LEARNING_RATE = 0.001
EPOCHS = 20
NUM_CLASSES = 2  # Binary classification (Lumpy skin detected or not)
```

1. Data Preprocessing

```
# Load the dataset
train_data, validation_data, test_data = rl.load_dataset("lumpy_skin_dataset_path")
# Preprocess the data
train_data = rl.preprocess_images(train_data, target_size=IMAGE_SIZE, normalize=True, augment=True)
validation_data = rl.preprocess_images(validation_data, target_size=IMAGE_SIZE, normalize=True, augment=False)
test_data = rl.preprocess_images(test_data, target_size=IMAGE_SIZE, normalize=True, augment=False)
```

2. Define the Model (MobileNetV2)

```
model = rl.MobileNetV2(input_shape=IMAGE_SIZE + (3,), include_top=False, weights="imagenet")
# Add a classification head
model = rl.add_dense_layer(model, units=NUM_CLASSES, activation="softmax")
```

3. Compile the Model

```
optimizer = rl.Adam(learning_rate=LEARNING_RATE)
loss_function = rl.categorical_crossentropy_loss()
metrics = ["accuracy"]
model.compile(optimizer=optimizer, loss=loss_function, metrics=metrics)
```

4. Train the Model

```
training_history = model.fit(
   train_data,
   validation_data=validation_data,
   epochs=EPOCHS,
   batch_size=BATCH_SIZE,
   shuffle=True,
   callbacks=[
rl.EarlyStopping(patience=3, monitor="val_loss"),
rl.ModelCheckpoint(filepath="best_model.h5",
save_best_only=True, monitor="val_accuracy")
   ]
)
```

5. Evaluate the Model

```
test_results = model.evaluate(test_data)
print("Test Accuracy:", test_results["accuracy"])
```

6. Save the Model

```
model.save("mobilenetv2_lumpy_skin_model.h5")
```

7. Inference Function

```
def predict(image_path):
   image = rl.preprocess_single_image(image_path, target_size=IMAGE_SIZE, normalize=True)
   prediction = model.predict(image)
   if prediction[0] > 0.5:
print("Lumpy skin detected.")
   else:
print("No lumpy skin detected.")

# Example Usage
predict("path_to_new_image.jpg")
```

VI. RESULTS AND ANALYSIS

Jupyter Note pad and Python 3.11.1 were utilized for the execution. To make and apply AI draws near, you might utilize Jupiter Note pad, an open-source program that coordinates information readiness, the execution of many AI calculations, and representation instruments. You might make and impart archives to live code, numerical conditions, pictures, maps, diagrams, perceptions, and story exposition utilizing Jupyter Note pad, an open-source, electronic intelligent climate. Python, PHP, R, C#, and a lot more dialects are among the numerous that it upholds. Coming up next are the specialized specs of the equipment: 512 GB of ROM and 8 GB of Slam on a 1.19 GHz Intel i5 tenth era PC. people with uneven skin contain 60% of the relative multitude of pictures in the public LSD dataset, though people with smooth skin contain 70%. The model is prepared utilizing 325 photographs of the information, and it is tried utilizing 700 photographs. Skin conditions are the principal focal point of this information assortment.

The informational collections should be the most important phase in any AI or LSD framework. The informational collections are vital for assessing and affirming the LSD framework's adequacy. Oftentimes, the datasets are isolated into two segments: one for testing and one for preparing. While the preparation set is the real informational collection used to prepare the model, the test set is utilized as contribution to the model to perform various undertakings.

The most exhaustive assessment of knotty skin issues is given by the LSD information assortment. A sensible number of records are remembered for both the test and train informational collections, making evaluation more straightforward and eliminating the need to pick explicit information from them. The assortment comprises of 1025 photos. The dataset's Table 1 records two different skin types: ordinary skin and uneven skin.

Table 1: Dataset Classes

Class	Images
Lumpy Skin	
Normal Skin	

The efficacy of several machine learning-based IDS is evaluated using the performance metrics mentioned below (Gao et al., 2019).

- True Positive (TP): If, after being detected, an attack is really being launched. Thus, only a trustworthy attack detection is a true positive.
- When an assault is identified but is not really an attack, this is known as a false positive (FP). This means that a false positive is only a false caution.
- Data that is correctly categorized as normal and is normal is known as a true negative (TN). Consequently, the true negative is a successful identification of a typical piece of data.

- A false negative (FN) is attack data that has been mistakenly categorized as normal. When no one is aware of the attack that has already taken place, it is the most dangerous scenario.
- Accuracy is defined as the ratio of the total number of observations to the sum of the true positive and negative values. Stated otherwise, the total number of correct classifications is usually determined by the accuracy.

Accuracy is a crucial performance parameter for evaluating the classifier. The accuracy formula is explained in equation 1.

The formula for accuracy is (TP+TN) / (TP+TN+FP+FN) … (1).

Equation 2 states that the ratio of true positive observations to the sum of true and false positive observations is the definition of accuracy.

The formula for precision is TP / (TP+FP) (2).

- How many accurate classifications are penalised by the number of missing elements is determined by the recall (sensitivity). The recall formula is discussed in Equation 3.

Recall = TP / (TP+FN) (3)

Specificity is the proportion of true negatives that the model correctly identifies. This implies that a higher proportion of real negatives, also known as false positives, which were previously believed to be positive, would be recorded. This percentage may also be referred to as a True Negative Rate (TNR).

The formula for TNR (specificity) is TN / (TN + FP) (4).

After the experiment's data has been pre-processed, the features selection methodology is used to identify the dataset's top 10 features, after which popular supervised and unsupervised learning techniques are used. In machine learning, XGBoost, Extreme Learning Machine (ELM), and Support Vector Machine (SVM) are used. The Efficient CNN subcategory includes the proposed MobileNetV2 model.

Figure 2: Instances in Dataset

The comparison between the suggested model and the state-of-the-art model is shown in Table 2.

Table 2: Experiment Results of Different Machine Learning Algorithms including the Proposed Model

Method	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
ESD [2]	89.00	89.89	90.00	89.80
M-SVM [2]	89.00	89.00	90	89.11
XGBoost [2]	90.01	89.00	89.25	89.92
ELM [2]	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.

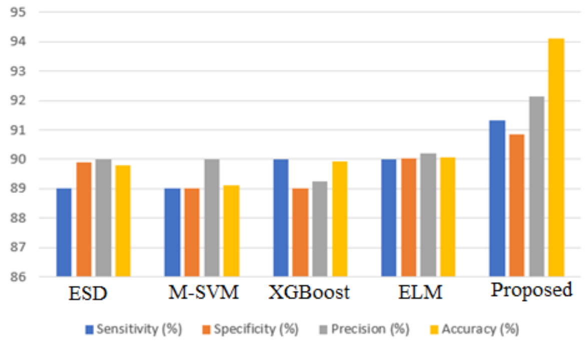

Figure 3: Performance Analysis of Different Models

CONCLUSION

A division and grouping model for cows with rough skin was given by this exploration. The system depicted an exchange learning methodology that utilized MobiltNetV2 with the ADAM enhancer. The proposed technique was assessed utilizing the notable datasets for the knotty skin condition in steers. F1-Measure, review, accuracy, and review are momentarily talked about to examine different sorts of administered and solo learning frameworks. In the wake of getting the LSD from the Kaggle library, it was analyzed and pre-handled utilizing the Fisher score procedure. This approach stays away from the over-fitting issue and lessens the dataset's component count. Both directed and unaided AI strategies are utilized to the pre-handled dataset. While contrasting the exhibition of the relative multitude of procedures, the troupe model performs better compared to some other model, even the cutting-edge model.

Future directions for the thesis include the following:

- To deliver an improved intrusion detection system solution by conducting a comprehensive examination of Deep Learning algorithms utilizing a real-time dataset.
- Investigating cutting-edge pre-processing techniques that might improve model accuracy.
- Deep learning techniques might enhance the LSD detection system's performance.

References

[1] Muhammad Saqib S, Iqbal M, Tahar Ben Othman M, Shahazad T, Yasin Ghadi Y, Al-Amro S, et al. (2024) Lumpy skin disease diagnosis in cattle: A deep learning approach optimized with RMSProp and MobileNetV2. PLoS ONE 19(8): e0302862. https:/

[2] 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).

[3] 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).

[4] 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.

[5] 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.

[6] 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.

[7] 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.

[8] 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.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

[13] 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.