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Swin-Base Transformer with Progressive Fine-Tuning and Test-Time Augmentation for Accurate Lumpy Skin Disease Detection in Cattle

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ABSTRACT

Lumpy is a contagious viral disease that affects cattle globally and, thus, causes significant financial loss ($2.4bn) globally. During 2022-2023, the loss for India itself is expected to be more than $2.4bn. Traditional methods for the diagnosis of Lumpy Skin Disease (LSD) rely on visual examination and laboratory tests which are time-consuming; subjective; or not easily accessible to rural communities. Because of this it is imperative that we develop an automated, accurate image based solution for diagnosing LSD in cattle. This paper proposes an image diagnostic framework that is based on a deep learning model known as Swin-Base Transformer that has been pretrained using weights from ImageNet-21K, and has been trained on a dataset comprised of 3,522 images of cattle skins (1,531 images of LSD affected cattle and 1,991 images of healthy cattle) collected from two Kaggle datasets. The proposed model is trained using a two-phase fine-tuning strategy, including different differential learning rates on a layer-by-layer basis, AdamW optimiser, cosine annealing learning rate scheduling, MixUp/CutMix regularizes and weighted cross entropy loss with label smoothing and 4×Test-Time Augmentation ensemble inference to maximise generalisation. The proposed framework has achieved an overall accuracy of 97.92% across both the training and testing datasets, as well as very good values for precision, recall, and F1-score. The confusion matrix analysis indicates that the model has very low misclassification rates between the healthy and infected classes. A ROC curve and Precision-Recall curve indicate that the model has excellent discriminative ability against the two classes (healthy and infected). Hence, the proposed model shows promise for providing accurate and reliable assistance to veterinarians in the field when diagnosing LSD in cattle.

KEYWORDS

Lumpy Skin Disease, Swin Transformer, Transfer Learning, Deep Learning, Cattle Disease Detection, Test-Time Augmentation, Veterinary Diagnostics.

1. INTRODUCTION

1.1 Background of LSD

Lumpy Skin Disease (LSD) is a highly contagious viral disease in cattle, causing serious disruptions to economies and agricultural systems worldwide (employment in agriculture). Since the initial introduction of LSD in India, it has rapidly spread throughout; as a result, large numbers of livestock have died, and livestock productivity has decreased dramatically. In 2022-2023, a stochastic model estimated total national economic loss at approximately INR 202,544 million ($2.44 billion) [1]. In addition, the impact of LSD has resulted in an estimated loss of INR 11,589 million in the state of Uttar Pradesh due to reduced milk production and impaired health of the cattle population [2]. All of these impacts clearly demonstrate that LSD is a significant threat to rural livelihoods and the dairy economy.

1.2 Limitations of Traditional Diagnosis

The LSD diagnosis currently requires visual examination, laboratory analysis and veterinary diagnosis which may be labour intensive and subjective. Nodule formation, fever and skin lesions are some clinical manifestations that may be confused with other diseases leading to inaccurate diagnosis or delayed diagnosis. Laboratory tests are also complicated and demand equipment and training which is not always available in rural areas. This delays the diagnostic process and implementation of control measures against the disease, resulting in disease spread and livestock industry losses [1].

1.3 Role of AI in Veterinary Disease Detection

Deep learning is an aspect of Artificial Intelligence (AI) that has the potential to be used to automatically detect diseases in veterinary medicine. Convolutional Neural Networks (CNNs) and Vision Transformers are examples of vision-based models that are very accurate in detecting disease symptoms in order to detect diseases early. AI models reduce the number of people working on a specific task, automate the process and allow making a diagnosis in time. According to a recent study, deep learning models can effectively identify LSD lesions with a high accuracy exceeding 97 per cent, which has a good prospect of being used in livestock health monitoring and sustainable farming practices [3].

1.4 Motivation for Study

The occurrence and prevalence of Lumpy Skin Disease (LSD) and the attendant economic losses emphasize the importance of effective and efficient diagnostic methods. Existing manual and laboratory methods may prove to be time-consuming, expensive and unavailable, especially to rural farmers. This compels the necessity of image based deep learning systems to detect and detect in time and in the correct location. The combination of cutting-edge architectures with explainable AI and rigorous validation methods can boost diagnostic accuracy, reduce costs and aid in early intervention, helping to improve livestock well-being and addressing key challenges in agriculture.

1.5 Aim and Objectives

The aim of the paper is to develop a very strong and generalised deep learning model to accurately classify cattle with Lumpy Skin Disease (LSD) into two categories using a Swin Transformer architecture. The objective of the study is to improve model performance by using progressive fine-tuning and stage-wise unfreezing of the backbone, advanced data augmentation, MixUp / CutMix regularizes and method(s) for handling class imbalance. The study will also incorporate increased prediction reliability through the use of cosine annealing learning rate schedules and test-time augmentation (TTA). To validate the efficacy and scalability of the proposed framework, it will be evaluated comprehensively using accuracy, precision, recall, F1 score, ROC curve and confusion matrix analysis.

1.6 Contribution of this Work

This article describes a two-phase progressive fine-tuning model utilizing the Swin-Base Transformer for classifying Lumpy Skin Disease (LSD) in dairy cattle through two different approaches staged backbone unfreezing with layer-wise differential learning rates for catastrophic forgetting. Many previously published methods utilized CNNs or ViT, which were either too complex or had too little performance. Our method also incorporates MixUp and CutMix data augmentation techniques as well as Weighted Random Sampling, cosine annealing schedule, and four different types of Test-Time Augmentation ensemble inference, all used together to develop a robust generalised model on limited amounts of veterinary imaging data. Extensive evaluations on multiple large datasets show our model is more sensitive and discriminative than previously existing models while also remaining clinically feasible for the actual population of animals diagnosed with early signs of LSD.

2. LITERATURE REVIEW

2.1 Related Works

The latest deep learning techniques have sped up the process of automated diagnosis of Lumpy Skin Disease (LSD) in cattle. The article by Ullah et al. [4] demonstrates the possibility of applying attention mechanisms in mobile applications, as the authors have created a Vision Transformer (ViT)-based mobile app that can be used to detect LSD at the earliest stage and with the highest accuracy. Saqib et al. [5] optimized MobileNetV2 with RMSprop, which is a fast approach with a high accuracy, and lightweight, which is ideal in resource-limited environments. Gouda and Abdallah [6] studied ensemble methods, comparing bagging and boosting approaches on multiclassimbalanced LSD data, and found that addressing the issue of class imbalance in the diagnosis of veterinary diseases is needed. Pal et al. [7] came up with a deep learning solution to the detection and classification of LSD with a veterinary-focused accuracy. Girmaw [8] used this to a variety of livestock skin diseases through the use of deep learning, generating generalized models of LSD. Muhammad et al. [9] developed new CNN models for automatic grading of bovine lumpy skin from images. Senthilkumar et al. [10] compared different pretrained models for early LSD detection, with EfficientNet showing high sensitivity. Alam et al. [11] developed an automatic LSD classification pipeline and Shakeel et al. [12] particularly focused on early LSD detection using CNNs for prompt disease management.

Abdullah et al. [13] showcased scalable and sustainable LSD detection using CNN. Mallikarjun and Narayana [14] used modified Capsule Networks for better spatial feature extraction for lesion classification. Shahab et al. [15] proposed an IoT-based monitoring system for LSD. Genemo [16] used deep learning features for predicting LSD risk areas. Olaniyan et al. [17] applied traditional machine learning for the prediction of LSD outbreaks. The latest development for LSD prediction is an AI-based multimodal approach using CNN, classical ML and large language models [18], which has been showing increased adoption in diagnosis.

Table 1. Comparative Analysis of Existing Methodology and Techniques

Author(s) & Year	Method Used	Performance	Key Finding
A. Ullah et al., (2026) [4]	Vision Transformer (ViT) + Mobile-based DL	98.12%	Requires high computational resources ; limited dataset diversity
S. M. Saqib et al., (2024) [5]	MobileNetV2 + RMSprop	95%	Small dataset, Poor generalization
H. F. Gouda & F. D. Abdallah, (2025) [6]	Ensemble ML (Bagging & Boosting)	82%	High Computational Cost, Not image-based; lacks DL advantages
M. Pal et al., (2025) [7]	ViT + ConvMixer + Ensemble	97%	Dataset imbalance, limited disease diversity.
D. W. Girmaw, (2025) [8]	EfficientNetB7, MobilNetV2, DenseNet201	97.08%	Not specific to LSD only
A.M. Muhammad et al., (2025) [9]	Deep CNN (Image Grading)	96.87%	Small datasets, Lack of standard benchmark
C. Senthilkumar et al., (2024) [10]	Transfer Learning (ResNet, VGG, MobileNet, DenseNet)	96.07%	Lacks real-world validation
F. Alam et al., (2025) [11]	InceptionV3 + SVM	84%	Lower than deep CNN accuracy
M. Z. Shakeel et al., (2024) [12]	CNN (Inception, Xception)	94.9%	Small dataset size, Overfitting risk.
W. Abdullah et al., (2025) [13]	CNN (DenseNet121, ResNet50V2, etc.)	90.36%	Limited robustness.
G. Mallikarjun & V. Narayana, (2024) [14]	Capsule Network	97.6%	Training instability Qualitative, Very Small dataset
H. Shahab et al., (2024) [15]	IoT + ML System	Qualitative	Hardware dependency
M. Genemo et al., (2023) [16]	CNN + Segmentation + ELM	94.1%	Limited scalability, Small Dataset
O. M. Olaniyan et al., (2023) [17]	Stacked Ensemble + Optimized ANN	89.5%	Not image-based
S. R. Janani et al., (2025) [18]	ML + CNN + LLM (Multimodal AI)	Qualitative	Early-stage research, No metrics

2.2 Research Gap Identified

Although there has been some improvement in the deep learning-based detection of Lumpy Skin Disease (LSD), there are certain limitations. Most studies rely mainly on CNN-based models [5][10][13] or transformer based models [4] to detect LSD without taking into consideration the issue of background noise or the localization of lesions. Although ensemble and multimodel models are better predictors [6][18], they do not necessarily provide timely and interpretable predictions. In addition, there is a low utilization of powerful validation methods such as cross-validation using K-Fold and under emphasis on explainable AI impact model trust and confidence to deploy [7][11].

3. METHODOLOGY

3.1 Pipeline Overview

The suggested end-to-end model includes five consecutive phases as shown in Fig. 1. Images of raw cattle skin are pre-processed and divided into training, validation and test subsets under four stratified split configurations. The MixUp and CutMix regularization, advanced spatial and colour augmentation, and Weighted Random

Sampling are used to deal with class imbalance in training. The Swin-Base Transformer backbone learns hierarchical multi-scale features with four progressive stages, and a classification head that produces binary LSD or healthy predictions. Lastly, at evaluation, 4xTest-Time Augmentation ensemble inference is used to maximize prediction robustness.

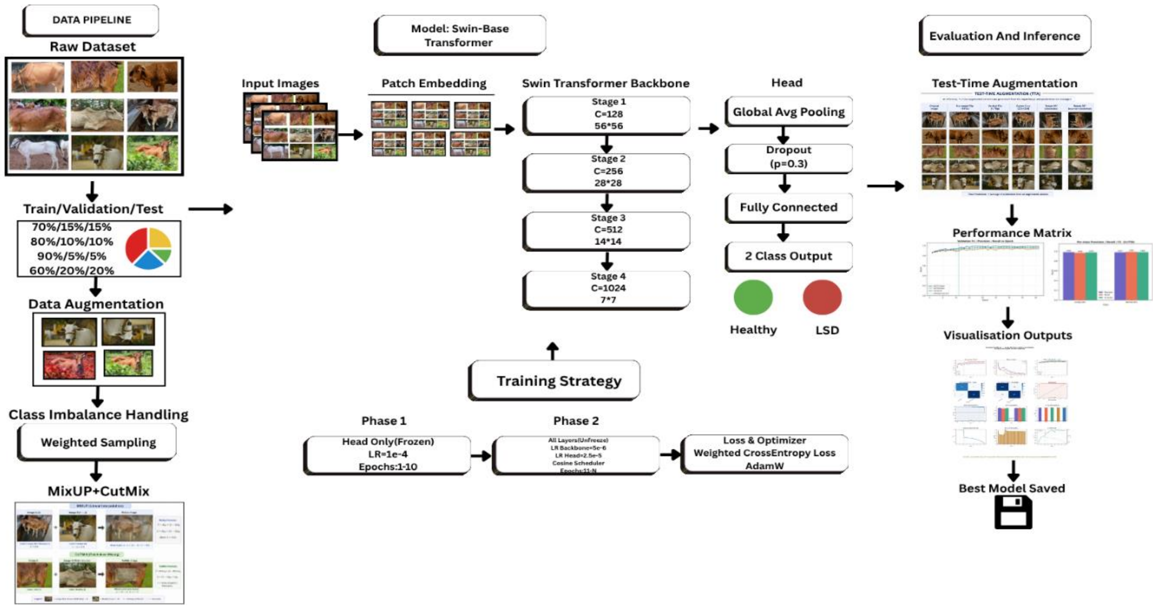

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Fig 1. Proposed end-to-end pipeline for Lumpy Skin Disease classification using a Swin-Base Transformer, illustrating data preprocessing, augmentation, class imbalance handling, two-phase training strategy, model architecture, test-time augmentation and final evaluation with performance metrics and visualization outputs.

3.2 Dataset Description and Sources

In building a deep learning model to diagnose LSD, we constructed a large image dataset by combining two publicly available datasets from Kaggle, the "Lumpy Skin Images Dataset" [19] and the "Lumpy Skin" dataset [20]. This combination allowed for increased visual variability in terms of cattle breed, skin colour, lesion severity, lighting and image quality - all important aspects when designing a diagnostic model for LSD.

Fig 2. Healthy and Lumpy Skin Cattle's Images

The merged dataset includes 3,522 images in total, from two categories: LSD-infected cattle skin and normal (healthy) cattle skin. The LSD class contains 1,531 images (1,207 from source [19] and 324 from source [20]), while the normal skin class contains 1,991 images (1,291 from source [19] and 700 from source [20]). The overall class distribution is shown in Table 2.

Table 2. Dataset Composition after Merging

Class	Lumpy Skin Images Dataset [19]	Lumpy Skin Dataset [20]	Total
LSD-Infected	1,207	324	1,531
Normal Skin	1,291	700	1,991
Total	2,498	1,024	3,522

3.3 Dataset Splitting

We divided the combined dataset into training set, validation set and test set using the stratified 70:15:15, 60:20:20, 80:10:10 and 90:05:05 split respectively to produce 2,465 training images, 528 validation images and

529 test images. We used stratified splitting to keep the class ratio in each subset as in the original dataset, and avoid class distribution shift between the subsets.

3.4 Class Imbalance Handling

The class imbalance is also low with a ratio of normal skin images of 1.30 times that of LSD-infected. Two methods were used to overcome this and were applied in the experimental code. To ensure that the minority class (infected with LSD) was equally represented in the batch, a larger sampling probability was applied to the minority in training, and the minority was represented in the batch. Second, the loss function (cross-entropy) was adjusted to place more weight on the minority group, which would increase the cost of misclassifying it. These precautions guarantee a model, which is not skewed towards the majority group.

3.5 Model Selection and Justification

Swin Transformer Base (swin_base_patch4_window7_224) was chosen as the main classification backbone because it has a hierarchical shifted-window self-attention strategy, which simultaneously considers local lesion texture and global cattle body context - a very important factor in the detection of LSD. In contrast to traditional CNNs, Swin-Base is trained to compute attention in non-overlapping local windows and gradually fuses patch tokens across stages, producing multi-scale feature representations that are highly adaptable to both scale and location of variable lesions on cattle skin. Its ImageNet-21K pretrained weights also allow powerful transfer of its features to the veterinary imaging field, diminishing the influence of limited domain specific training data.

3.6 Transfer Learning and Two-Phase Fine-Tuning Strategy

ImageNet-21K pretrained weights are used to initialize the model and are trained in two phases with a progressive fine-tuning approach to avoid catastrophic forgetting and stabilize convergence. During Phase 1 (epochs 110) the Swin backbone is frozen and the classification head only trained with 1 x 10 -4 learning rate, where the randomly initialized head can adjust without corrupting trained representations. During Phase 2 (epochs 11–50), the backbone is completely unfrozen and the backbone layer-wise differential learning rates are set to backbone layer: 5×10 -6 and classification head: 2.5×10 -5 (5x the backbone rate), as is customary in other Vision Transformer fine-tuning [4][10].

3.7 Training Configuration and Optimization

Table 3 summarizes the entire training set-up. Weight decay of 1×10^{-4} is used in both stages with the AdamW optimizer. The loss criterion is weighted cross-entropy (label smoothing=0.05) to mitigate against overconfidence and the class weight is inverted frequency of class weight to counter the 1.30:1 imbalance in the classes. In each phase, a Cosine Annealing learning rate scheduler (η min = = 1×10^{-8}) is used. This is done with gradient clipping (max norm = 1.0) to avoid exploding gradients. AMP training is employed on CUDA to speed up calculations. The best validation F1-score is used to select a model, and early stopping happens when 12 consecutive epochs have not improved the model.

Table 3. Training Hyperparameter Configuration

Parameter	**Value**
Framework	PyTorch + timm
Backbone	swin_base_patch4_window7_224
Pretrained weights	ImageNet-21K
Input resolution	224 × 224
Batch size	16
Max epochs	50
Phase 1 LR (head)	1×10^{-4}
Phase 2 LR (backbone)	5×10^{-6}
Phase 2 LR (head)	2.5×10^{-5}
Optimizer	AdamW (weight decay=1×10^{-4})
LR Scheduler	CosineAnnealingLR

Loss function	CrossEntropy + label smoothing (ε=0.05)
Dropout rate	0.3
Drop path rate	0.2
Early stopping patience	12 epochs
Unfreeze epoch	10
TTA views	4× (original, H-flip, V-flip, center-crop)
Random seed	42

3.8 Test-Time Augmentation Ensemble

Four augmented images of every test image are created at inference of standard resize, horizontal flip, vertical flip, and resize with centre-crop. Results the final prediction is the average of the four forward passes softmax probability vectors, which enhances the resilience to positional and orientational variability in field-acquired cattle images.

3.9 Evaluation Metrics

To comprehensively assess model performance on the binary LSD classification task, the following standard metrics were computed on the held-out test set using 4×TTA ensemble predictions.

3.9.1 Accuracy measures the overall fraction of correctly classified samples:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

3.9.2 Precision quantifies the proportion of positive predictions that are truly positive:

$$Precision = \frac{TP}{TP + FP}$$

3.9.3 Recall (Sensitivity) measures the model's ability to correctly identify all true LSD-infected samples:

$$Recall = \frac{TP}{TP + FN}$$

3.9.4 F1-Score is the harmonic mean of Precision and Recall, providing a balanced metric under class imbalance:

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

3.9.5 AUC-ROC quantifies the area under the Receiver Operating Characteristic curve, measuring discriminative ability across all classification thresholds:

$$AUC = \int_0^1 TPR(FPR)\ d(FPR)$$

3.9.6 Average Precision (AP) summarizes the Precision-Recall curve as a weighted mean of precision values at each recall threshold:

$$AP = \sum_n (R_n - R_{n-1}) \cdot P_n$$

where TP = True Positives, TN = True Negatives, FP = False Positives, and FN = False Negatives.

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4. RESULTS AND DISCUSSION

4.1 Experimental Results

Table 4. Experimental Results obtained from Swin Transformer model when Train Validated and Tested on Multiple Split Ratios

Training Validation Testing Ratio	Model Used	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
90:05:05	Swin Transformer	97.74	96.12	100.0	98.02
80:10:10		97.73	97.04	98.99	98.01
70:15:15		97.92	97.73	98.69	98.21
60:20:20		97.87	97.50	98.73	98.11
Average		**97.81**	**97.09**	**99.10**	**98.08**

4.2 Confusion Matrix Analysis

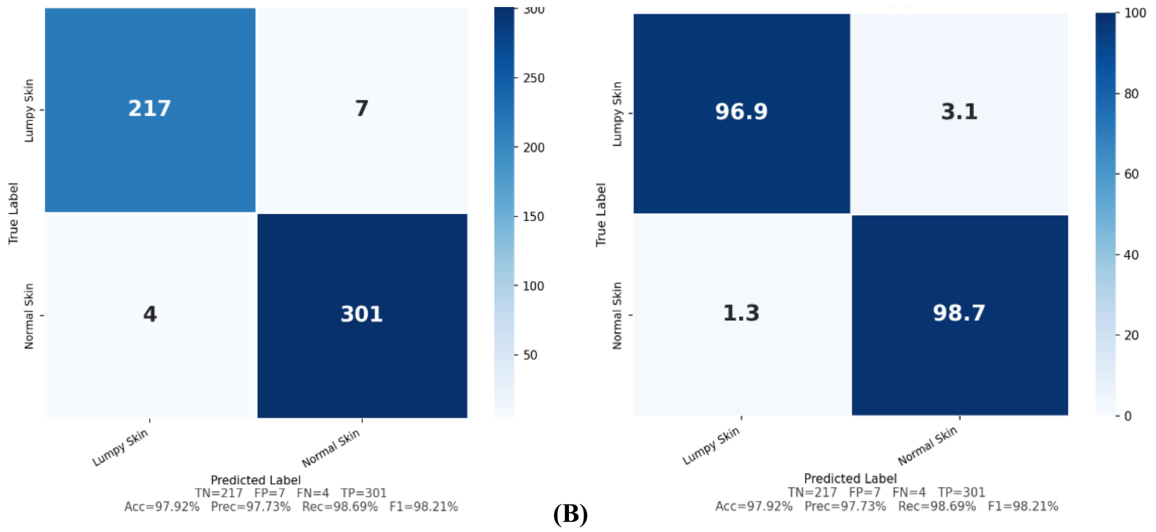


Fig 3. (A) Confusion Matrix and (B) Normalize Confusion Matrix of Primary Split (70:15:15)

4.3 ROC and Precision-Recall Curve

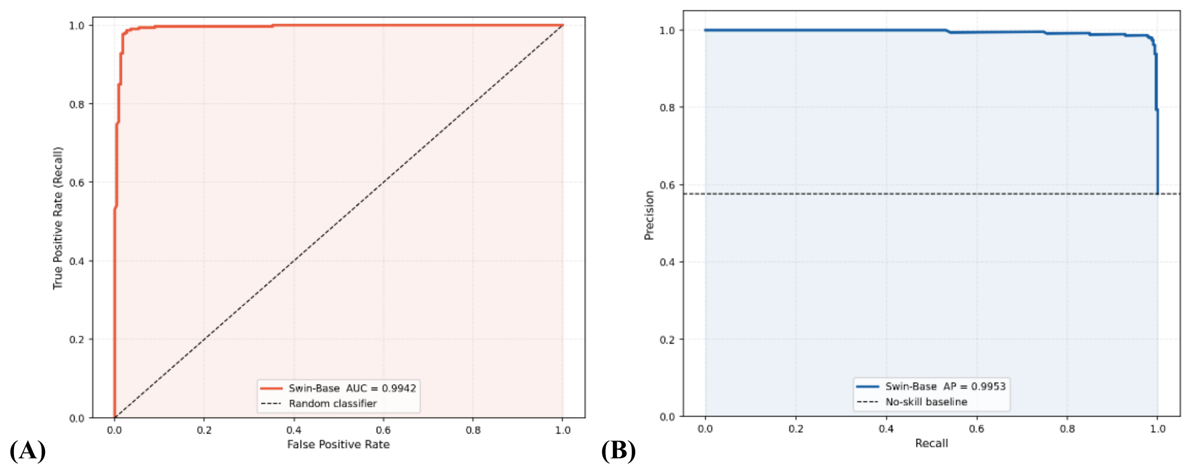
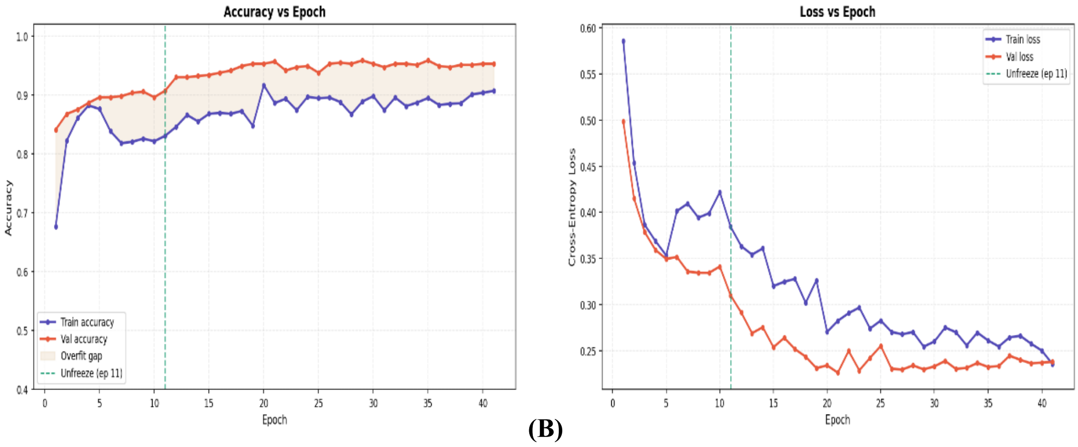


Fig 4. (A) ROC and (B) Precision –Recall Curve of Primary Split (70:15:15)

4.4 Accuracy vs Epoch and Loss vs Epoch



(A) **(B)**

Fig 5. (A) Accuracy vs Epoch and (B) Loss vs Epoch of Primary Split (70:15:15)

4.5 Limitations

Although the suggested Swin-Base framework has shown good results, there are a few limitations that should be mentioned. First, the merged dataset only contains 3,522 images sourced through 2 Kaggle repositories, which, although sufficient to validate proof-of-concept, lacks the geographical and breed level diversity needed to robustly generalize across the different cattle populations, climatic regions, and LSD outbreak strains that occur in different parts of the world. Second, the dataset has only two classes (LSD-infected vs. normal skin), excluding intermediate levels of disease severity and co-occurring skin conditions such as dermatophilosis or ringworm, which are similar to LSD in its early stages and may cause major misclassification in real-world veterinary practice. Third, the existing structure only works with static 2D RGB images, and fails to incorporate multimodal clinical indicators like body temperature, behavioural patterns, or time course imaging, which practising veterinarians routinely use to make a differential diagnosis. Fourth, Swin-Base architecture with 87.8M parameters incurs heavy computational overhead, making it impossible to directly deploy the model on resource-constrained edge devices, such as mobile phones or IoT-based farm cameras which have not been addressed in the current work.

5. COMPARITIVE ANALYSIS

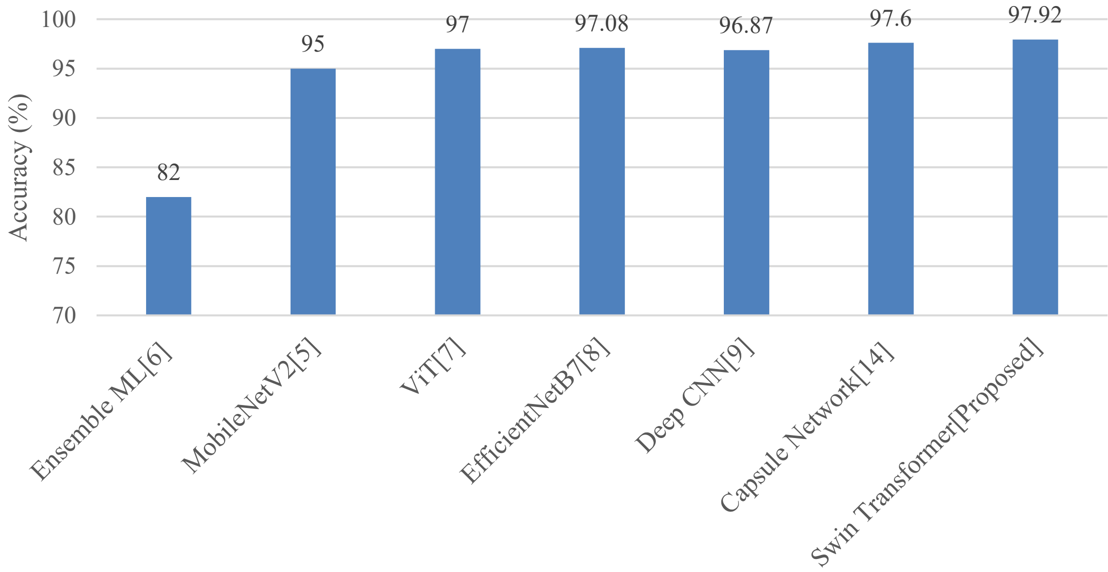


Fig 6. Comparative Analysis of Proposed Methodology with Existing Methodology

6. CONCLUSION AND FUTURE SCOPE

6.1 Conclusion of the Study

This work shows that a framework built on the Swin Transformer and progressively fine-tuned can be used for binary classification of Lumpy Skin Disease in cattle. The use of advanced augmentation methods, MixUp, CutMix regularization, class weighting, and cosine annealing all help improve how well the model generalises to new data. Also, one can use Test-Time Augmentation to enhance prediction robustness and obtain high accuracy, precision, recall and F1-score values. An exhaustive evaluation of the model performance based on ROC curves and confusion matrices demonstrated that the model was able to effectively distinguish between uninfected and infected animals. These results demonstrate the models suitability for use in real-world veterinary practice and can be seen as a scalable and efficient method to aid with early detection of disease and allow for timely intervention in order to decrease the economic consequences associated with livestock production.

6.2 Future Work

Future studies will concentrate on enhancing the robustness and clinical use of the suggested Swin Transformer model. Automatic lesion detection models such as YOLO-based localization models can contribute to the improvement of the classifier's accuracy. The addition of Grad-CAM techniques to this approach will provide visual cues about the areas of an image that the model focuses on; thus aiding in interpretability. Extending this pipeline with k-fold cross-validation and testing on an external dataset would create better generalizability across broader regions. Further expanding to include multiple complementary classes in the classification pipeline will also support the need for enhanced performance during the deployments within the veterinary sector and increasing the number of validated datasets used for training would allow for more realistic variability in the real-world vet field.

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