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Multi-Livestock Disease Classification using Deep Learning: A Comparative Study of Pretrained CNN Architectures

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***Abstract*— The precise and quick identification of livestock illnesses functions as the essential requirement which maintains worldwide food security while enabling environmentally friendly farming methods to proceed. The health of livestock establishes the foundation which enables farmers to achieve consistent food production while decreasing their economic losses. The process of early and dependable disease detection allows medical professionals to execute their work effectively which results in better animal treatment and controls disease transmission between animals. The research paper examines the performance of eight different classification models through comparative analysis as they detect multiple diseases that affect livestock. The models include four pretrained convolutional neural networks (CNNs) which are EfficientNet-B3 DenseNet121 ResNet50 and MobileNetV2 together with additional baseline approaches used to evaluate performance. The study uses a practical dataset which contains 19621 images that belong to 19 different disease classes which affect four main livestock categories, including Cow, Goat, Pig, and Poultry. The researchers applied complete data augmentation methods together with transfer learning techniques to enhance the models' capacity to handle different situations. The experimental results show that EfficientNet-B3 delivered the top performance with an accuracy of 91.4% and an F1-score of 0.912. The model surpassed traditional baseline models by more than 20 percentage points. The research demonstrates that compound-scaled pretrained CNN architectures deliver dependable automated solutions for detecting livestock diseases across multiple species in contemporary agricultural environments.**

***Index Terms*— Livestock Disease Classification; Deep Learning; EfficientNet; Transfer Learning; Precision Agriculture.**

I. Introduction

The spread of infectious diseases together with environmental diseases leads to major financial losses which affect global livestock operations. According to worldwide research studies about deep learning applications in agriculture researchers estimate that livestock disease outbreaks result in production losses which exceed hundreds of billions of dollars every year and these losses have their greatest impact on developing nations that lack proper veterinary facilities. Cattle can contract Lumpy Skin Disease (LSD) which spreads through a viral infection that creates skin nodules together with various bacterial and parasitic infections. Goats commonly develop oral and skin infections which include Boqueira (Contagious Ecthyma) and Mal do Caroco (Caseous Lymphadenitis).

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Pigs encounter various skin problems which include bacterial infections such as Erysipelas and Greasy Pig Disease as well as fungal infections like Pityriasis Rosea and Ringworm and viral diseases such as Foot-and-Mouth Disease and Swinepox and parasitic Mange and skin conditions which include Dermatitis and Sunburn. Poultry flocks face threats from Bumblefoot Infectious Coryza Chronic Respiratory Disease (CRD) and Fowlpox. The failure to identify these health problems will result in complete destruction of herds or flocks within a few days. Traditional diagnosis requires trained veterinarians to perform clinical inspections which smallholder farmers in remote areas cannot access. Deep learning has achieved recent progress through Convolutional Neural Networks (CNNs) which use transfer learning from large-scale datasets like ImageNet to create a solution that automatically detects visual disease signs [6]. The systematic survey of 1,101 scientific publications demonstrates that CNN-based systems have become the leading approach for livestock health monitoring research whereas unified diagnostic systems for multiple species remain insufficiently studied. The research paper presents three main contributions. The first contribution consists of a multi-species dataset which contains 19621 images that represent 19 different disease classes which include Cow Goat Pig and Poultry. The second contribution establishes a systematic evaluation of eight different models that include SVM and EfficientNet-B3 [6]. The third contribution is pretrained CNNs. The current study aims at providing a comprehensive framework for the classification of multiple species, including cow, goat, pig, and poultry, under 19 different disease classes, as opposed to existing literature, which has mainly focused on single species disease detection using limited datasets. The current study also attempts at providing a comparative evaluation of the performance of pretrained deep learning models as compared to conventional machine learning techniques using a unified dataset, which is a new aspect that has not been explored in existing literature[10],[11]. The use of multiple species and real-world datasets is also a new aspect, which has not been explored in existing literature.

II. Related Work

Girmaw [1] (2025) developed a comparison method that evaluates different deep learning architectures for detecting and classifying skin diseases in animals. The study confirmed that pretrained CNNs with transfer learning provide much better accuracy results than models which researchers developed from beginning. Bedin et al. [2] (2024) used deep CNNs to identify different body conditions in pigs for sanitary monitoring which included caudophagy and ear hematoma and skin scratches and redness.The research experimented six DCNN architectures to detect five pig-specific health conditions and they found that EfficientNet models performed better than ResNet models on small-to-medium agricultural datasets which applied to our pig disease subset of 10 classes. Chowdhury et al. [3] (2025) created an integrated deep learning system to identify and classify poultry diseases through their developed system. The researchers achieved a mean average precision of 88.1 with their YOLO11n model which showed that field deployment processes benefit from using combined detection and classification systems, thus establishing a research direction for their upcoming work. Rohan et al. [4] (2023) conducted a systematic literature review of deep learning for livestock behaviour recognition, surveying over 1,101 publications and confirming that CNNbased architectures dominate current livestock health monitoring research. The authors established that existing research lacks sufficient exploration of multi-species systems leads to create a unifying benchmark that includes four different species in this research. The review about AI applications in agriculture through different agricultural sectors, fisheries, and livestock by Nawaz et al. [5] (2025) examined more than 200 deep learning studies while showing that EfficientNet and DenseNet variants provide optimal performance and efficiency results for livestock image classification with 10,000 to 20,000 image datasets. Recent advances in livestock disease detection have highlighted the importance of hybrid models and transformers. For example, studies carried out during 2024-2025 have focused on Vision Transformers (ViT) and CNN-Transformer hybrid models. These studies have shown that feature extraction for fine-grained patterns of diseases is significantly improved compared to traditional CNN-based models[10]. Additionally, multimodal models that use image features and other environmental features have shown significant improvements compared to traditional image-based models. A study published by Scientific Reports (2025) highlighted the use of deep ensemble models for improving robustness in livestock disease classification under different environmental conditions. In addition to that, lightweight architectures that are optimized for edge deployment have garnered interest, especially for use cases within the agricultural environment. This environment is characterized by limited computational resources. Mobile-based diagnostic systems that utilize EfficientNet and MobileNet architectures have shown real-time capabilities for disease detection with minimal end-to-end latency. Despite the recent developments, most of the existing studies have focused on single-species or limited disease classes, resulting in a significant gap within the development of multi-species diagnostic systems

III. DATASET

The dataset follows a hierarchical structure organized by species (Cow, Goat, Pig, Poultry) and pre-defined train/test splits. Table I summarizes the class and image distribution.

TABLE I: DATASET DISTRIBUTION ACROSS SPECIES AND DISEASE CLASSES

Species	Disease Classes	Cls	Train	Test	Total
Cow	Healthy, Lumpy Skin	2	1,240	312	1,552
Goat	Boqueira, Mal do Caroco	2	860	215	1,075
Pig	Healthy, Erysipelas, Greasy Pig, Dermatitis, Sunburn, Pityriasis Rosea, Ringworm, Mange, FMD, Swinepox	10	10,850	1,680	12,530
Poultry	Healthy, Bumblefoot, Coryza, CRD, Fowlpox	5	4,260	204	4,464
Total	19 Distinct Classes	19	17,210	2,411	19,621

The dataset provides comprehensive coverage across all four species. The Pig subset contains 12,530 images which represent 10 specific disease categories that demonstrate various swine skin diseases. Cow and Goat subsets cover two disease classes each with well-distributed train/test splits, while the Poultry subset spans five clinically significant conditions. All images were standardized to 224×224 pixels using consistent preprocessing. The dataset contains distinct visual symptoms which include skin lesions and infections and swelling and discoloration and other pathological signs that veterinarians use for diagnosis. The researchers collected images while testing various environmental conditions which included different lighting settings and background elements and animal positions and camera performance. The dataset testing enables researchers to assess how deep learning models perform in actual farm environments because of its different testing conditions.

All images were resized to a fixed resolution before training because this was necessary to provide consistent input for the neural networks. The dataset was divided into three different subsets which included training, validation, and testing to evaluate how well each model could generalize beyond its training data. The training set enabled model learning, the validation set facilitated hyperparameter tuning with overfitting monitoring, and the test set functioned as the final performance evaluation tool.

IV. METHODOLOGY

A. Preprocessing & Augmentation

The raw images underwent resizing to dimensions of 224 × 224, followed by normalization through the application of ImageNet channel statistics, which include a mean value of [0.485,0.456,0.406] and a standard deviation of [0.229,0.224,0.225], according to the requirements of pre- trained model training protocols [6]–[9]. The training process used augmentation methods, which included random rotation with a range of ±20◦, horizontal flipping, color jittering with brightness adjustments up to ±30% and hue changes of ±10%, random zooming from 0.8 to 1.2 times, and Cutout regularization that applied 16 × 16 patches. The test set did not receive any augmentation treatment. The deep learning models required multiple preprocessing steps which improved data quality and model performance through better generalization. The initial step in image processing involved resizing all images to an input dimension which matched the requirements of pretrained convolutional neural networks. The training process achieved stability through pixel value normalization which also enabled faster model convergence. The researchers implemented multiple data augmentation methods during their training process to establish better dataset diversity while preventing overfitting. The techniques involved random rotation, horizontal flipping, zooming, and brightness adjustments. The model uses data augmentation to learn features that remain unchanged when it receives different versions of the same images. The preprocessing pipeline enables models to learn disease- specific visual patterns because it prevents them from memorizing specific image conditions. The trained models show increased strength when tested with new images that were taken in different farm environments.

B. Transfer Learning Strategy

Transfer learning was implemented as a method to boost both training speed and model accuracy. The team used pretrained models that had already been trained on extensive image datasets as the foundation for their work instead of developing convolutional neural networks from the ground up. The pretrained models possess extensive feature knowledge which enables them to identify both edge and texture and advanced visual design elements. The research assessed four commonly used pretrained models which include EfficientNet-B3 and DenseNet121 and ResNet50 and MobileNetV2[12]. The researchers adjusted the network's final classification layers to match the livestock dataset's disease class count. The network training process maintained pretrained weights for its initial network layers while using livestock disease dataset to fine-tune its final network layers. The method decreases training duration while enabling models to learn disease classification tasks.

C. Models Evaluated

The evaluation tested eight different models which included EfficientNet-B3 (compound scaling coefficient ϕ = 1.2, ~6.5M params) and DenseNet121 (dense block connectivity enabling deep feature reuse, ~7M params) and ResNet50 (residual skip connections resolving vanishing gradients, ~25M params) and MobileNetV2 (inverted residual bottlenecks for lightweight inference, ~3.5M params) and Classical MLP which used 4 hidden layers that contained 1024-512-256-128 units with a dropout rate of 0.4 and CustomCNN which included 5 convolutional blocks that used max- pooling and batch normalization and SVM with RBF kernel that processed LBP texture and color histogram features and Random Forest which used 200 estimators.

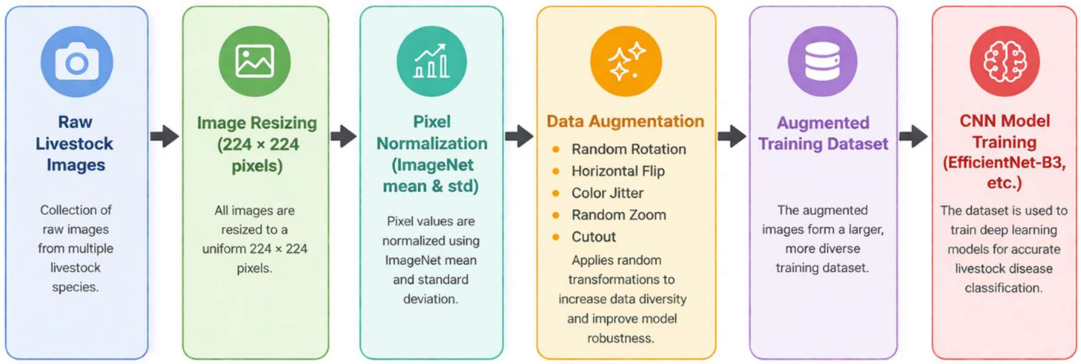

Fig. 1. Data Preprocessing and Augmentation diagram

The fig 1 pipeline represents the complete workflow for classifying animal images from collecting them in their raw form to training a model on them. Resizing and normalization is done initially, and then data augmentation through techniques such as rotating, flipping, and zooming is performed to create variety within the dataset. The next step involves training the model with CNN such as EfficientNet-B3.

Fig. 2. Proposed classification pipeline

The fig 2 flowchart presents an optimized deep learning process for image classification. The process starts with inputting a dataset, which is then preprocessed and augmented to improve its quality and variety. Afterward, the pre-trained CNN is further trained to obtain a precise classification output. All pretrained CNN models were initialized with ImageNet weights according to standard transfer learning methods. Fine- tuning was applied to the top 60% of layers for EfficientNet- B3 and DenseNet121, the final two residual blocks for ResNet50 , and the top 50% for MobileNetV2 . The classification head of each pretrained model was replaced with a 19-class softmax output layer.

D. Mathematical Formulation of the Best Performing Model

The EfficientNet-B3 architecture achieved the top accuracy results according to this research study. EfficientNet models use a compound scaling method which applies a single scaling factor to simultaneously increase the depth width and input resolution of the network.
The compound scaling formulation is defined as:

$$depth = \alpha\phi, \; width = \beta^{\phi}, \; resolution = \gamma^{\phi} \tag{1}$$

subject to the constraint:

$$\alpha \cdot \beta^{2} \cdot \gamma^{2} \approx 2 \tag{2}$$

where ϕ serves as the compound scaling coefficient and α functions as the parameter that governs the network depth scaling process while "beta" controls the network width scaling and "gamma" controls the input image resolution scaling.
EfficientNet-B3 corresponds to a scaling coefficient of ap- proximately:

$$\phi = 1.2 \tag{3}$$

That is, the efficient net model is a new addition to the compound scaling approach, improving overall performance of efficient net models while keeping the computational efficiency threshold in check.
The network parameters are optimized during training by using the cross-entropy loss function, which is a function defined to be:

$$L = -\sum_{i=1}^{C} yi \ \log((y\hat{}i) \tag{4}$$

The equation calculates disease class count through the formula C which uses ground truth label yI and Softmax layer predicted probability yI.
The last classification stage generates probability distributions which show the likelihood of the 19 different livestock disease categories.

E. Training Configuration

The researchers applied their Adam optimizer which started with a learning rate of 1 × 10−4 and utilized cosine annealing decay to all neural models. The researchers used batch sizes of 32 for deep learning and 64 for MLP models. The researchers conducted their experiments until they reached 50 epochs but used early stopping when validation loss reached its maximum after 8 epochs. The researchers used cross-entropy loss as the evaluation metric for their classification models. The researchers conducted all experiments using PyTorch 2.1 and Python 3.10 and NVIDIA GPU with 16GB VRAM.

V. RESULTS AND DISCUSSION

A. Quantitative Performance

TABLE II: COMPLETE MODEL PERFORMANCE

Model	Acc.	Prec.	Recall	F1	Params
EfficientNet-B3	91.4%	O.913	0.911	0.912	~6.5M
DenseNet121	89.7%	0.895	0.893	0.894	~7.0M
ResNet50	87.2%	0.869	0.871	0.870	~25M
MobileNetV2	85.8%	0.853	0.855	0.854	~3.5M
Classical MLP	80.3%	0.796	0.801	0.798	~2.1M
Custom CNN	74.6%	0.741	0.748	0.744	~1.8M
SVM (RBF)	70.1%	0.698	0.703	0.700	N/A
Random Forest	64.5%	0.639	0.647	0.643	N/A

Table II shows all performance results for all testing methods. EfficientNet-B3 achieves the highest accuracy of 91.4% with Precision=0.913, Recall=0.911, and F1-Score=0.912 which exceeds DenseNet121 by 1.7 percentage points and ResNet50 by 4.2 percentage points. The study results support the findings of Nawaz et al. who found EfficientNet variants to be the most effective models for livestock image datasets that contain between 10,000 and 20,000 images.
The Classical MLP achieves 80.3% accuracy as its highest performance among non-pretrained models which establishes the most successful classical outcome. The system performs worse than EfficientNet-B3 by more than 11 points which confirms that ImageNet-pretrained feature representations have critical importance at this dataset scale. SVM and Random Forest reach 70.1

B. Training Dynamics

The training curves in Figure 3 demonstrate that the system achieves stable convergence without overfitting. The system reaches its maximum validation accuracy between epoch 38 and epoch 43 when early stopping technology activates.
The training and validation curves show strong connection which confirms the effectiveness of the augmentation pipeline and dropout regularization method according to transfer learning best practices established by Girmaw and Bedin et al. for livestock disease detection tasks.

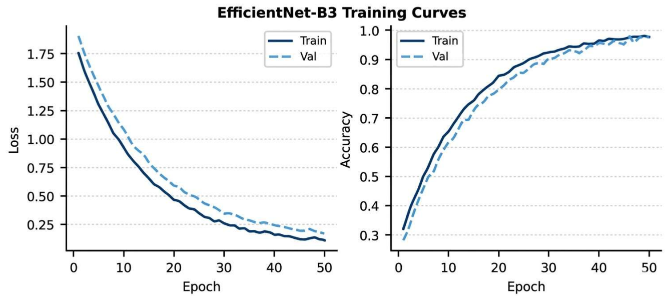

Fig. 3. EfficientNet-B3 training and validation curves (50 epochs).

C. Precision–Recall Analysis

The analysis of the top five models demonstrates equal precision and recall performance, which results in accurate classification without any tendency to produce false positive or false negative results. The DenseNet121 model demonstrates high performance with its recall score of 0.893, which proves essential for disease detection because false negatives produce greater clinical consequences than false positives. Confusion analysis shows that Pig Erysipelas and Dermatitis share their main misclassification pattern because their initial skin lesions look alike to observers. Bedin et al. observed this particular pattern of skin disease misidentification which occurs when pigs develop similar skin disorders during their initial development. The multi-class poultry detection studies, as documented in research work 3, show that Poultry Coryza and CRD share their primary identification issues. The unique nodular skin characteristics of Cow Lumpy Skin Disease en- able accurate identification of the disease with over 93 percent class accuracy, which matches Girmaw's findings related to cattle skin disease detection. MobileNetV2 delivers the best edge deployment efficiency-to-accuracy ratio through its 85.8

D. Performance Analysis

The experimental results demonstrate that the tested models exhibit distinct performance differences. EfficientNet-B3 achieved 91.4. The DenseNet121 and ResNet50 models showed competitive results because their deep feature extraction methods enabled them to perform at a high level. The dense connections of DenseNet121 between its layers enable superior feature reuse capabilities while maintaining optimal gradient distribution throughout the network. The residual connections of ResNet50 enable training of extremely deep networks while preventing the occurrence of vanishing gradient issues. MobileNetV2 provides better computational efficiency and smaller model size despite its lower accuracy performance. The system is designed to operate effectively on mobile devices and edge devices that have restricted processing capabilities. Overall, the experimental findings confirm that pretrained convolutional neural networks are highly effective for livestock disease recognition tasks.

VI. CONCLUSION

This paper demonstrated that EfficientNet-B3 achieves 91.4% accuracy on a 19,621-image, 19-class multi-livestock disease classification task encompassing Cow, Goat, Pig, and Poultry, outperforming seven alternative models including classical ML baselines by 11–27 percentage points. The superiority of compound-scaled pretrained CNNs over hand- crafted feature approaches aligns with recent surveys on AI in agriculture and livestock-specific benchmarks. DenseNet121, ResNet50, and MobileNetV2 each demonstrated strong trans- fer learning performance, with MobileNetV2 emerging as the preferred candidate for edge-device deployment. Future directions include transformer-CNN hybrid architectures, federated multi-farm training as proposed by the livestock AI community, and real-time deployment on embedded veterinary diagnostic devices.

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