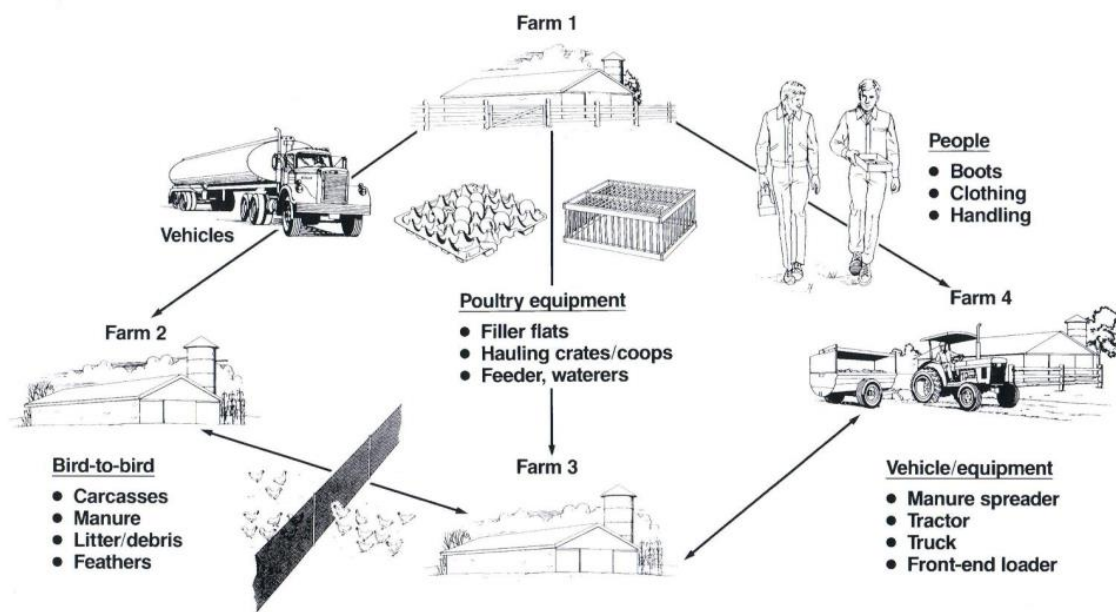# Transfer Learning-Based Classification of Poultry Diseases for Enhanced Health Management

Project Documentation Format

Introduction : The industry 4.0 is driving transformative changes in agricultural industry, integrating information technology, automated production systems, and digital optimisation techniques. This technological shift aligns with significant demographic trends, i.e., it has been reported that global population projections suggest a rise to 9.6 billion people by 2050, along with rapid urbanization and shifting consumption patterns that are significantly boosting demand for poultry products [1]. The poultry industry faces particular pressure for transformation, with annual production volumes projected to exceed 180 million tonnes by 2050 [2]. While increased production is essential to meet global demand, it also introduces risks, such as heightened vulnerability to disease outbreaks in densely populated poultry farms. These high-density environments, coupled with complex supply chains, create ideal conditions for the spread of pathogens, making robust disease surveillance and management systems a necessity, primarily via the use of automation.

ARCHITECTURE :

How Poultry Disease Spreads

Farm 1

Vehicles

People
- Boots
- Clothing
- Handling

Farm 4

Poultry equipment
- Filler flats
- Hauling crates/coops
- Feeder, waterers

Farm 2

Bird-to-bird
- Carcasses
- Manure
- Litter/debris
- Feathers

Farm 3

Vehicle/equipment
- Manure spreader
- Tractor
- Truck
- Front-end loader

USDA United States Department of Agriculture
Animal and Plant Health Inspection Service

Disease Alert Number
APHIS 91–55–66
Issued June 2002

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Fig. 1. Sample images from each dataset class.

Table 1. Dataset distribution.

Class	Original	Augmented	Total
Coccidiosis	2103		2103
Healthy	2057		2057
Newcastle	376	1787	2163
Salmonella	2276		2276

A significant class imbalance was observed in the initial dataset, particularly concerning the Newcastle disease class, which contained substantially fewer images (376) compared to other classes (>2000 each). This imbalance could potentially bias the model training process and reduce classification performance for the underrepresented class [16].

This approach resulted in a balanced dataset where each class contained approximately 2100 images, facilitating unbiased model training. Quality control measures were implemented throughout the augmentation process to verify that the generated images maintained clinical relevance and diagnostic features.

Feature extraction: Transfer learning model

The transfer learning process on pre-trained models and external classifiers involved the following steps with transfer learning architectures:

1 . Initialize and load pre-trained model weights: Begin by initializing a pre-trained deep learning model, with weights trained on the ImageNet dataset. These weights provide a robust foundation of learned features from extensive prior training. The pre-trained model will serve as a feature extractor, so the final classification layers will be omitted or ignored.

2 . Freeze the classification layers in the pre-trained model: To preserve the learned feature representations, set the layers in the pre-trained model to non-trainable. This step prevents any changes to the weights during subsequent steps, ensuring that the feature extraction leverages the generalized patterns learned from ImageNet.

3 . Extract features from the pre-trained model: Pass the new dataset through the pre-trained model, stopping at one of the final layers before the original classification layers. This will produce a set of feature vectors for each image, capturing high-level representations of the input data. Store these extracted features for use in the classification stage.

4 . Train an external classifier on the extracted features: Using the extracted feature vectors as input, train a machine learning classifier such as Support Vector Machine (SVM), Logistic Regression (LR), k-Nearest Neighbors (KNN) or a similar model.

5 . Evaluate model performance on a test set: Finally, evaluate the performance of the combined feature extraction and classifier pipeline on a test set. Assess metrics like accuracy, precision, recall, and F1-score to gauge the classification effectiveness. Fine-tune the classifier parameters or revisit feature extraction settings if necessary to further optimize results.
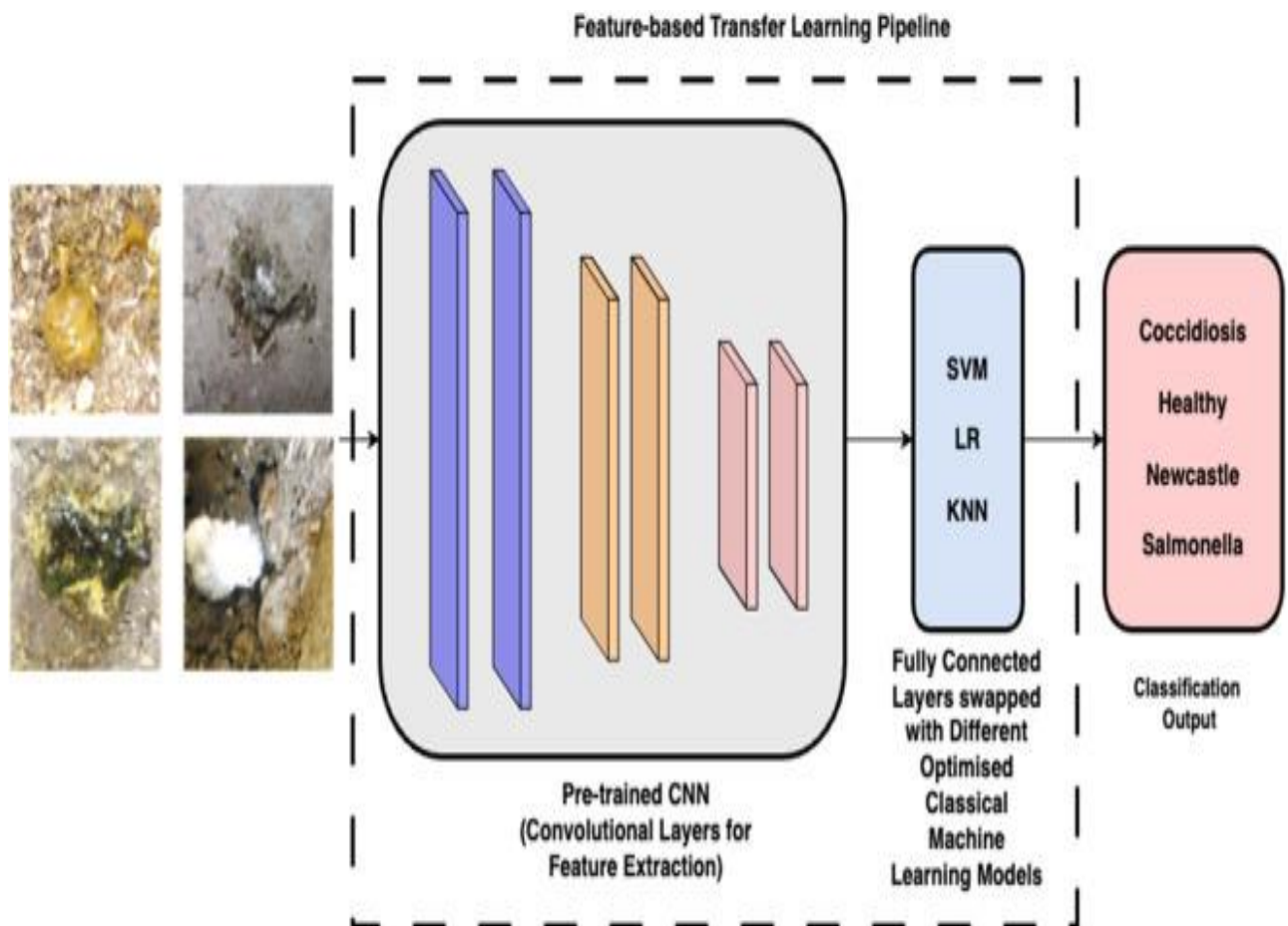
Fig. 2. Feature-based transfer learning methodology adopted for the poultry disease classification.

Results and discussion :

The performance of various transfer learning models combined with distinct classification techniques was assessed in terms of CA on the training, validation, and test sets, as presented . The results highlight each model's ability to accurately classify images across different sets. For further evaluation, precision, recall, F1-score, and individual class accuracy were calculated for the top-performing model-classifier pipelines.

1 . DenseNet201 and ResNet152 combined with SVM and LR demonstrated the highest overall accuracy across the validation and test sets, with validation and test CA scores consistently above 97 %.

2 . InceptionV3 and InceptionResNetV2 also displayed high CA values, particularly when used with SVM and LR classifiers, suggesting that these architectures are well-suited to the classification task.

3 . Models such as MobileNetV3Small and VGG19 performed reasonably well, with accuracy ranging from 83 % to 97 % depending on the classifier used, though performance decreased slightly with KNN.

4 . Overall, DenseNet201 and ResNet152 with SVM or LR classifiers emerged as the most consistent and high-performing combinations.

Graphical Representation :
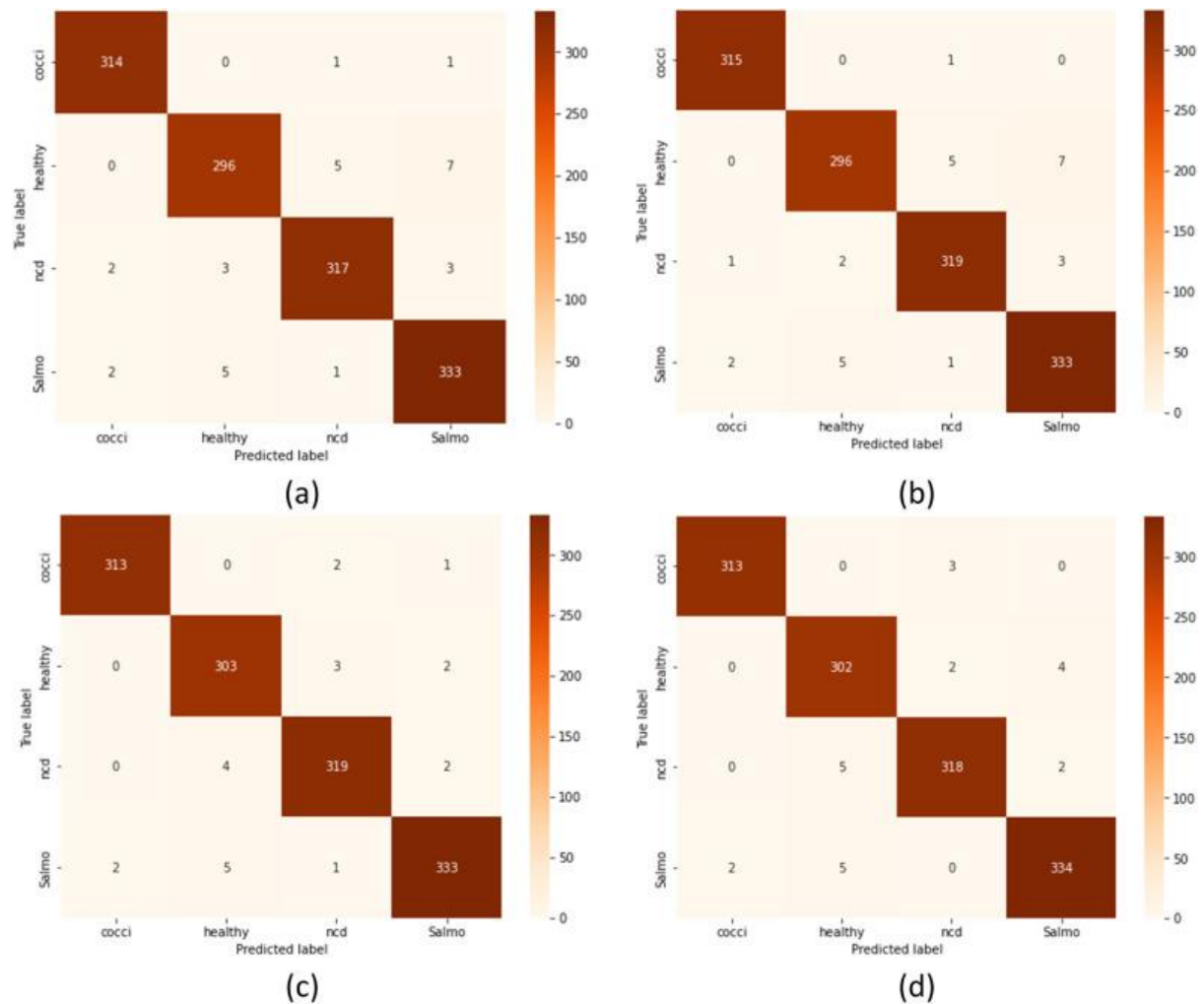
Fig. 3. Confusion matrix of the pipelines developed on the test dataset (a) DenseNet201-SVM (b) DenseNet201-LR (c) ResNet152-SVM and (d) ResNet152-LR.

Conclusion :

In this study, we conducted experiments with various transfer learning architectures in combination with traditional classifiers for classifying poultry disease images. Specifically, we implemented and evaluated DenseNet201, ResNet152, InceptionV3, and MobileNetV3Small models paired with SVM, LR, and KNN classifiers. The results demonstrated that pre-trained CNN architectures perform particularly well with the given dataset, especially DenseNet201 and ResNet152, when integrated with SVM and LR classifiers. Both DenseNet201 and ResNet152 achieved classification accuracies exceeding 97 % on both validation and test datasets. These pipelines demonstrated robust and reliable performance across all classes, with minimal misclassifications, as illustrated in the confusion matrices. This emphasises their capacity to effectively extract discriminative features essential for accurate disease identification.

In comparison, while InceptionV3 and MobileNetV3Small also achieved satisfactory classification results, their performance exhibited greater variability across classifiers. Notably, the KNN classifier consistently underperformed relative to SVM and LR, indicating that distance-based approaches are less effective for this dataset. Among all combinations, the ResNet152-SVM pipeline outperformed its counterparts, demonstrating its potential as an optimal solution for poultry disease classification tasks.