Food Safety Innovation

Risk Management with AI

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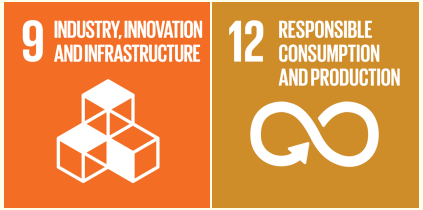
Introduction

- Food security concerns, driven by the projected global population growth to over 9.6 billion by 2050, have necessitated an increase in agricultural production. However, environmental constraints and a shift towards animal-based food proteins have led to a decline in per-capita cereal production and an anticipated 70% increase in global meat consumption by 2050. This rising demand has resulted in intensive and extensive animal production, posing challenges in animal health, welfare, and environmental sustainability.
- To address these challenges, Precision Livestock Farming (PLF) has emerged as a solution, leveraging efficient automated systems to monitor various bio-processes and responses related to animal welfare, health, and productivity. Traditional human surveillance has become insufficient, making PLF crucial in livestock monitoring.
- Vision-based PLF systems, utilizing computer vision technology, have gained prominence due to advancements in technology. These systems offer non-intrusive, non-invasive, and effective monitoring, allowing for data recording and analysis while reducing labor-intensive processes. Computer vision involves applying mathematics, computer science, and software programming to achieve image-based automated process control.
- There are two categories of computer vision-based systems: machine learning-based and deep learning-based. Machine learning-based systems follow a typical image processing procedure, while deep learning-based systems use Deep Neural Networks (DNN) for classification or regression. Computer vision tasks include image identification, object detection, image classification, semantic segmentation, and specific object recognition.
- In poultry monitoring, computer vision systems play a crucial role, with applications such as image identification, object detection, and semantic segmentation. The main components of a computer vision system include the camera sensor, image processing board, software, and hardware. These systems use various sensors, including visual light-based (CCD and CMOS), thermal, and infrared (IR) sensors, to capture and process information for effective poultry monitoring.



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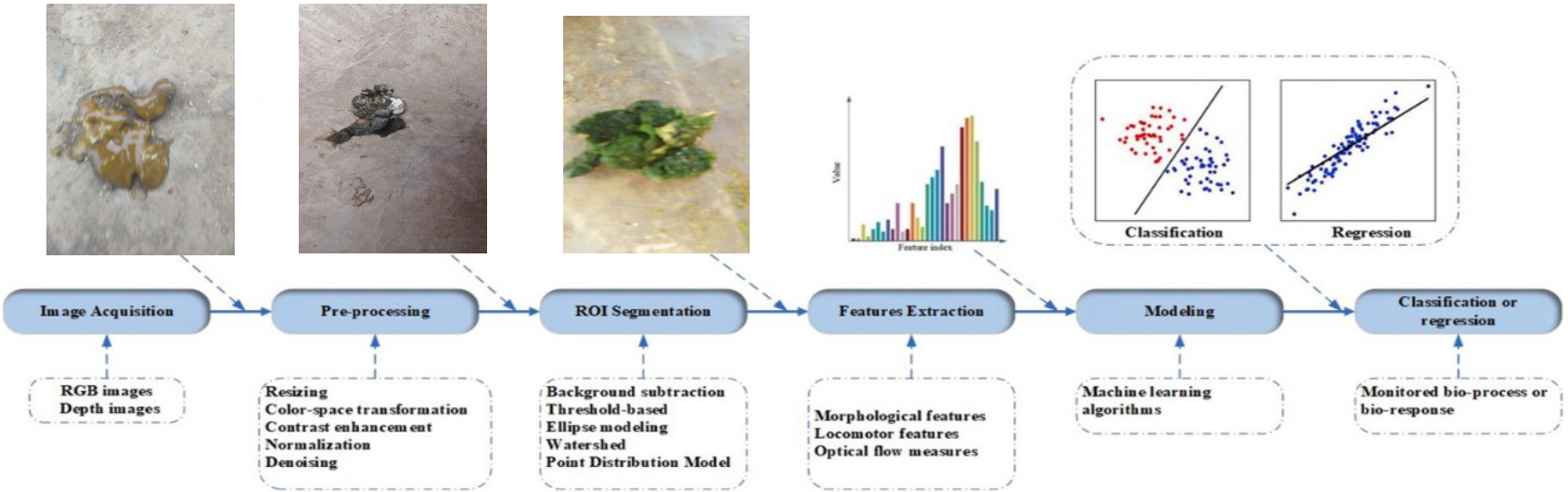
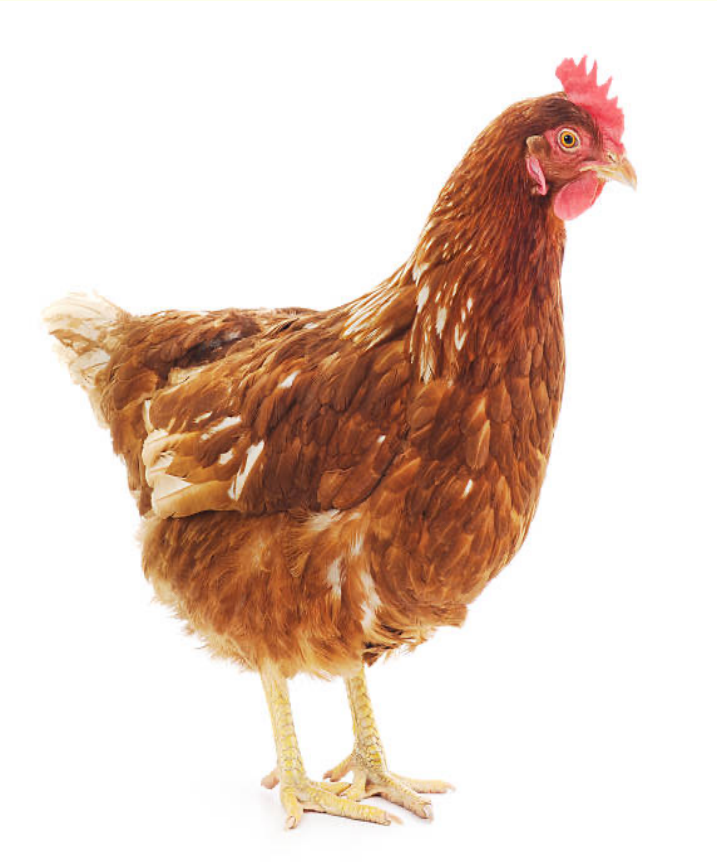
01 Problem Statement





01 - Problem Statement
Smart farm, Chicken Market and Poultry Disease

Challenge:

- Small to medium-scale farms face a significant challenge in implementing proper surveillance due to limited manpower and knowledge.
- The lack of resources for effective monitoring poses a risk of diseases spreading unchecked, emphasizing the importance of early detection for control and prevention.

Issue:

- Small and medium-sized farms often struggle to allocate sufficient personnel and expertise for comprehensive surveillance.
- In the absence of robust monitoring systems, there is a heightened risk of diseases spreading rapidly within these farms.

Importance of Early Detection:

- Early detection is crucial for controlling and preventing the spread of diseases on farms.
- Implementing efficient and straightforward methods for early detection is essential to curb the impact of diseases and ensure the health and productivity of the livestock.

Solution:

- Developing and implementing user-friendly and efficient surveillance systems that cater to the specific challenges faced by small to medium-scale farms.
- Integrating technologies like Precision Livestock Farming (PLF) with user-friendly interfaces to enable easy monitoring and early disease detection.
- Providing training and support to farmers to enhance their knowledge and empower them to use surveillance tools effectively.

Overall, addressing the challenges faced by small to medium-scale farms in terms of surveillance requires a tailored solution that combines accessible technology and educational support to facilitate early detection and disease control.


A picture is worth
a thousand words

Chickens Poops

Cocci

Coccidiosis is a protozoal disease causing diarrhea, ,weight loss and decreased production in poultry. It can be fatal. Prevention is key and is achieved with use of anticoccidials or vaccination. Diagnosis is by fecal flotation to detect oocysts, often in combination with characteristic necropsy findings.

Healthy

Normal' droppings consist of faeces and urates. Digestive waste is the solid brown or greyish portion of the poop that's usually firm enough to hold its shape. The faeces are capped with white urate. A healthy chicken passes this 'normal' poo around 12 to 15 times a day, including at night.

Chickens Poops

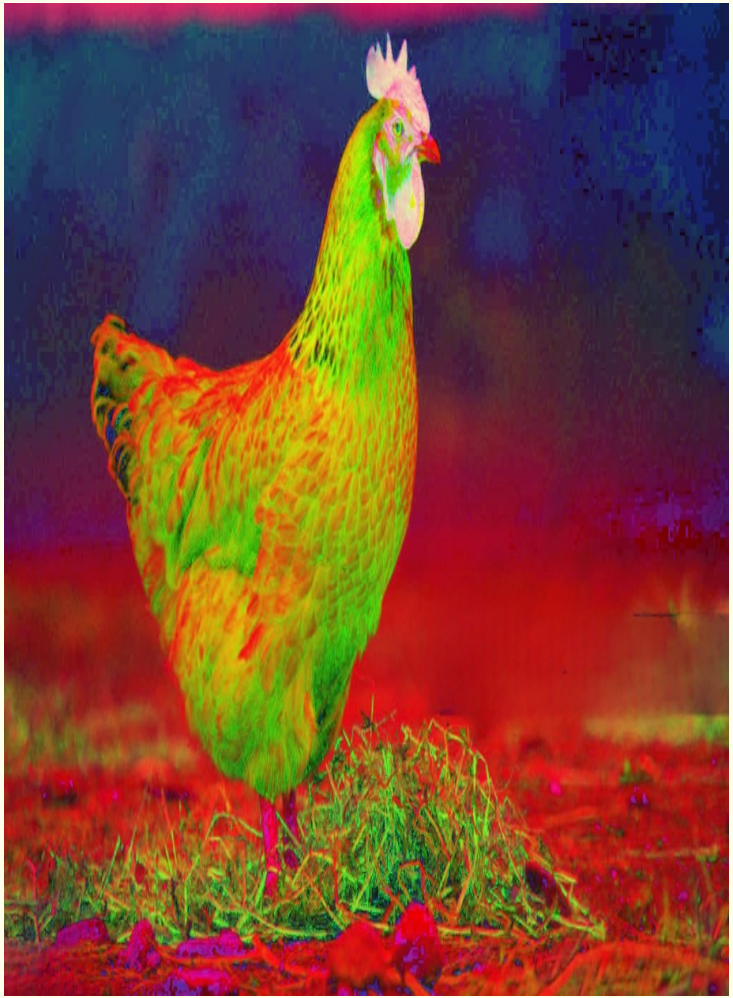
Cocci

Healthy

Ncd

Salmo

“Prevention Is Better Than Cure” – The Dutch philosopher Desiderius Erasmus. In this project, we aim to develop an applicatio that can help to detect the disease of chickens via chicken fecal by deep learning neural network.”



2- Data Gathering

Information of Dataset and Image Processing

Class	No. Picture
Cocci	PCR: **374** Farm: **2,476**
Healthy	PCR: 347 Farm: 2,404
NCD	PCR: 186 Farm: 562
Salmo	PCR: 349 Farm: 2,625

Total picture: **8,607 Pictures**
Size of all picture: **13.3 GB**

This is a series if information about poultry disease diagnostics that was annotated

- Polymerase Chain Reaction(PCR) – by Lab
- Farm-labeled fecal image

2- Data Gathering

Information of Dataset and Image Processing

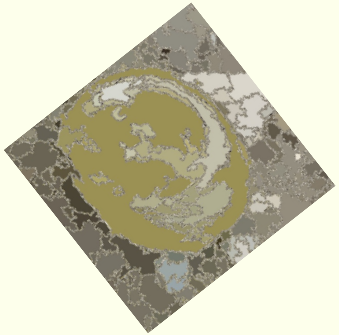
Class	Train	Valid	Test
Cocci	1,997	247	232
Helathy	1,903	276	225
NCD	450 + 1800	54	58
Salmo	2,096	239	290

- In balance class NCD class
- Image Augmentation

Image Augmentatiton

Origin image

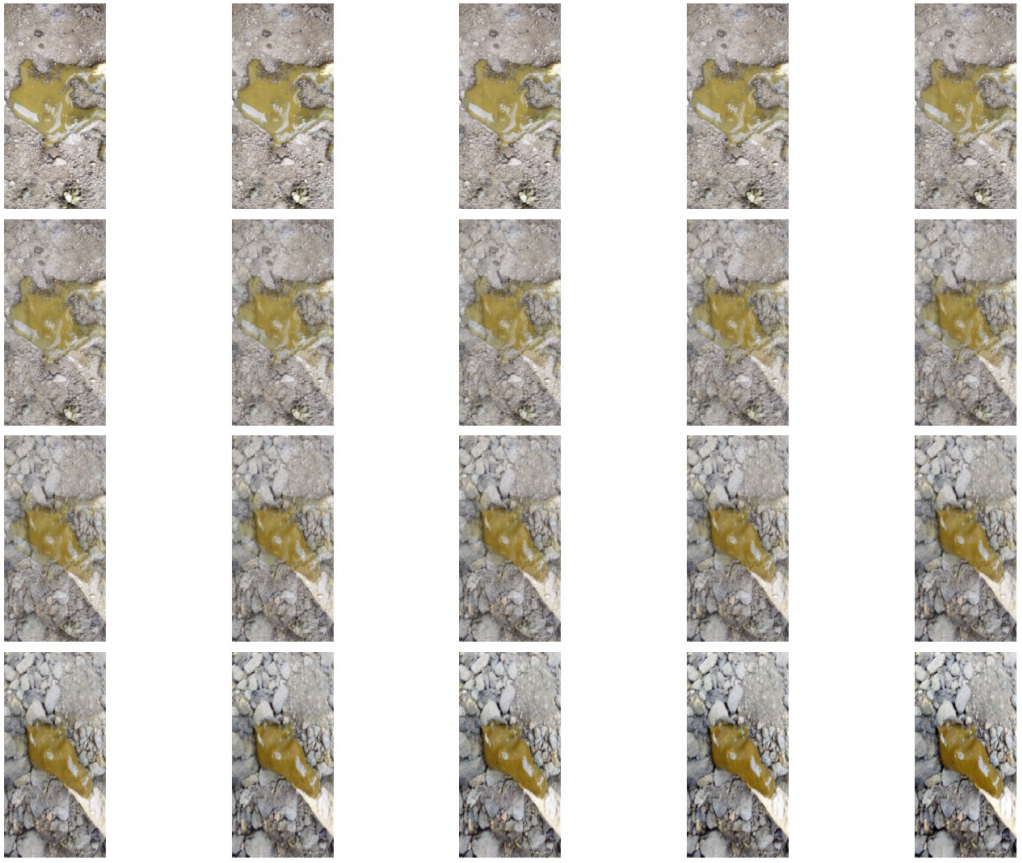
Flip image



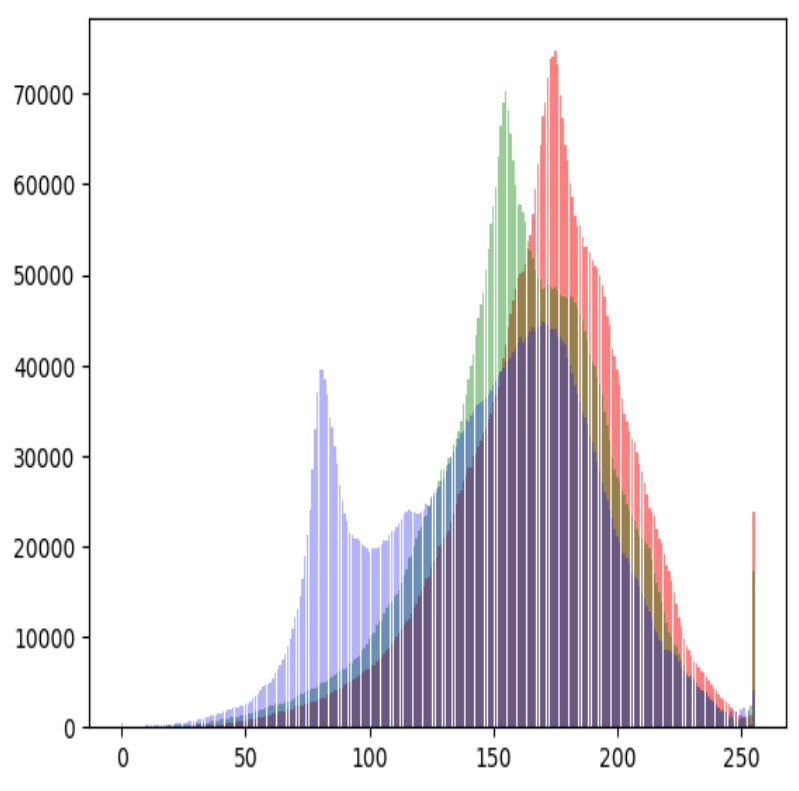
Shift and Rotate image

Noise and Contrast

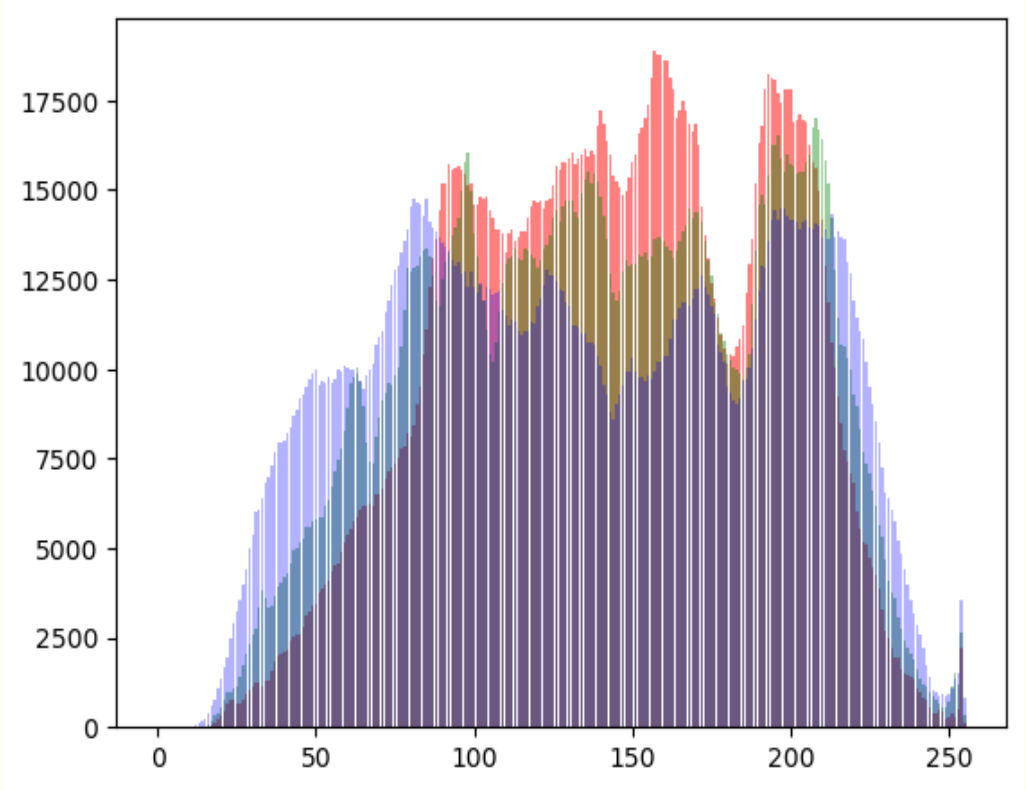
Interpolate between the two images



Plotting the histograms of pixel values for the RGB channels of an image

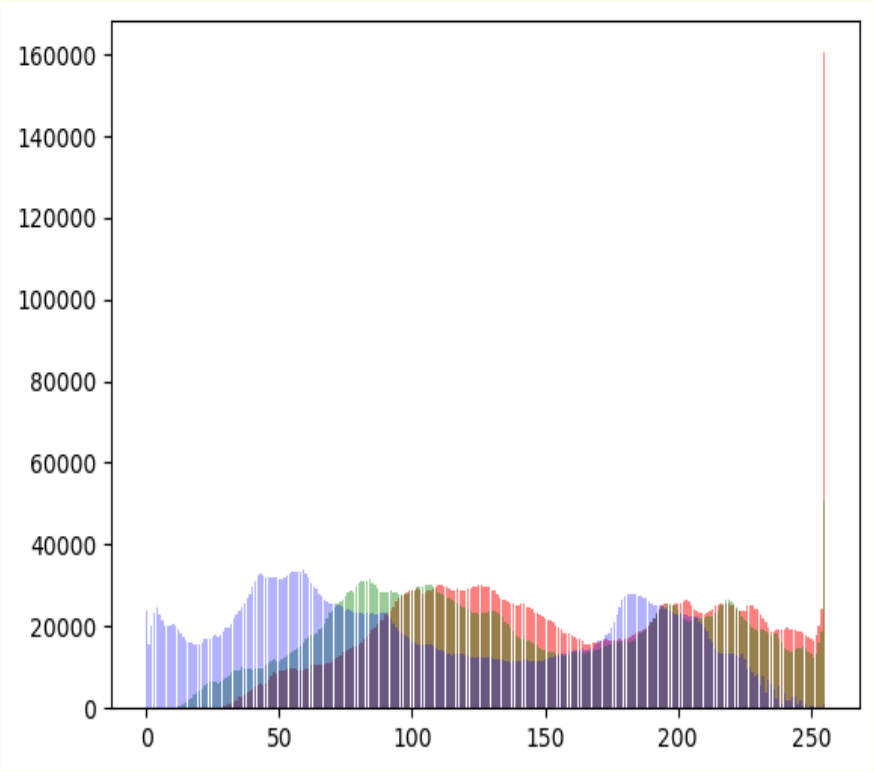


Cocci

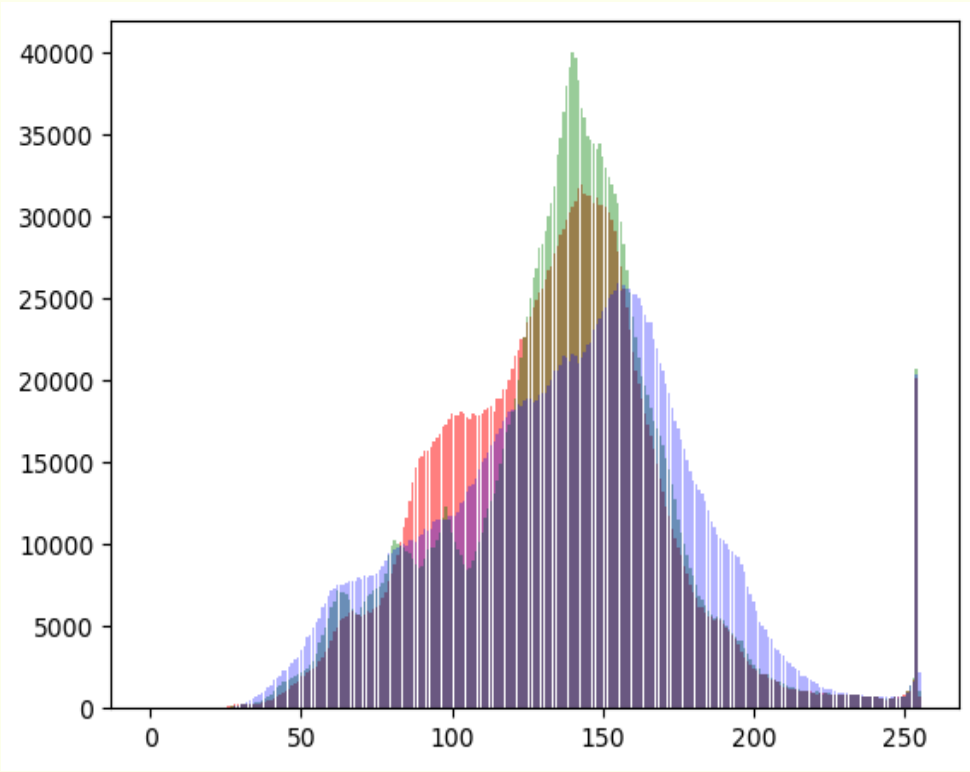


Healthy

Plotting the histograms of pixel values for the RGB channels of an image



NCD

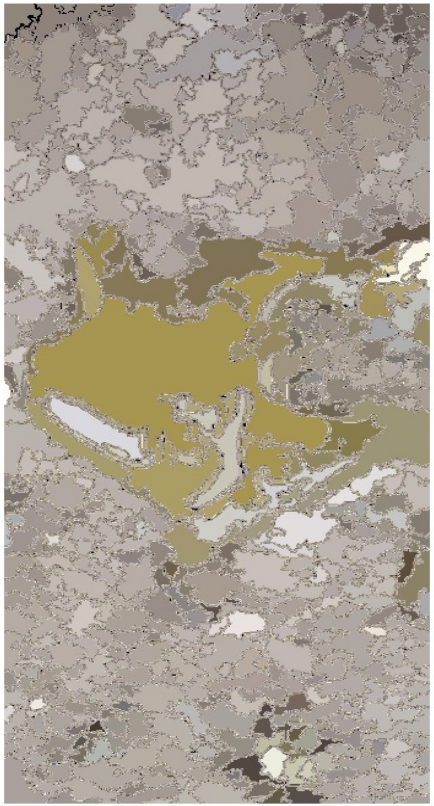


Salmo

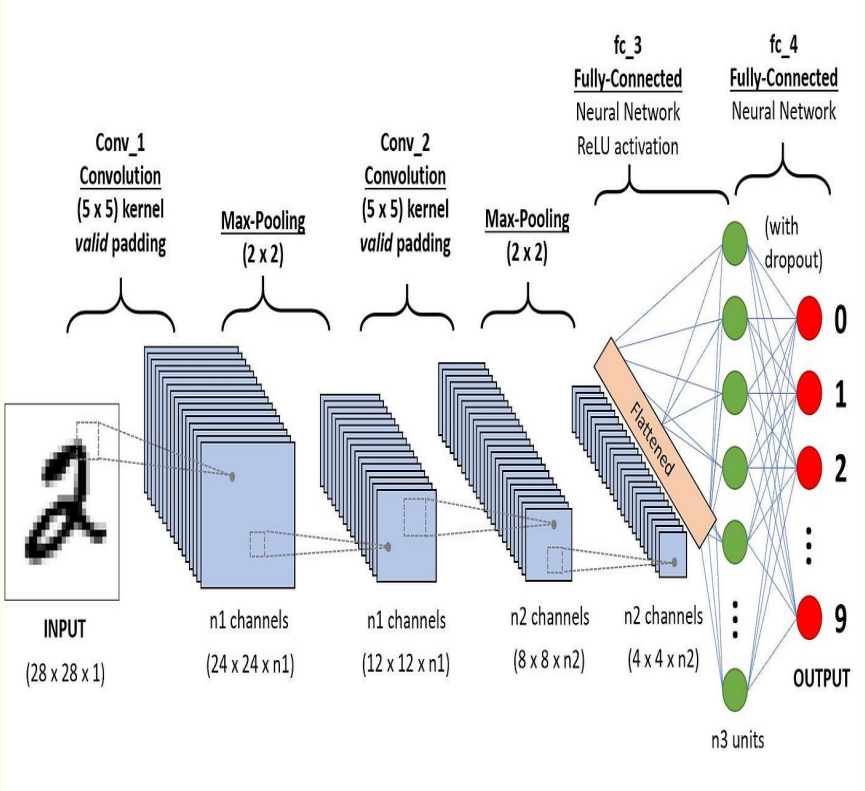
Image Segmentation

Original

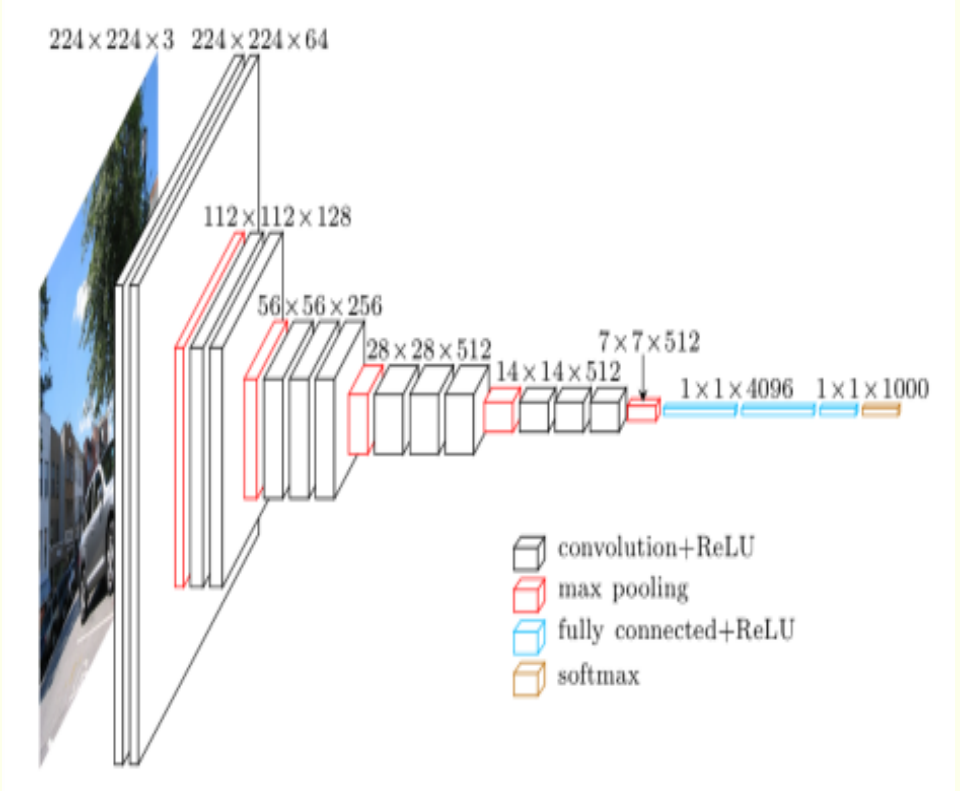
Segmented with Felzenszwalb's method



Model Traning



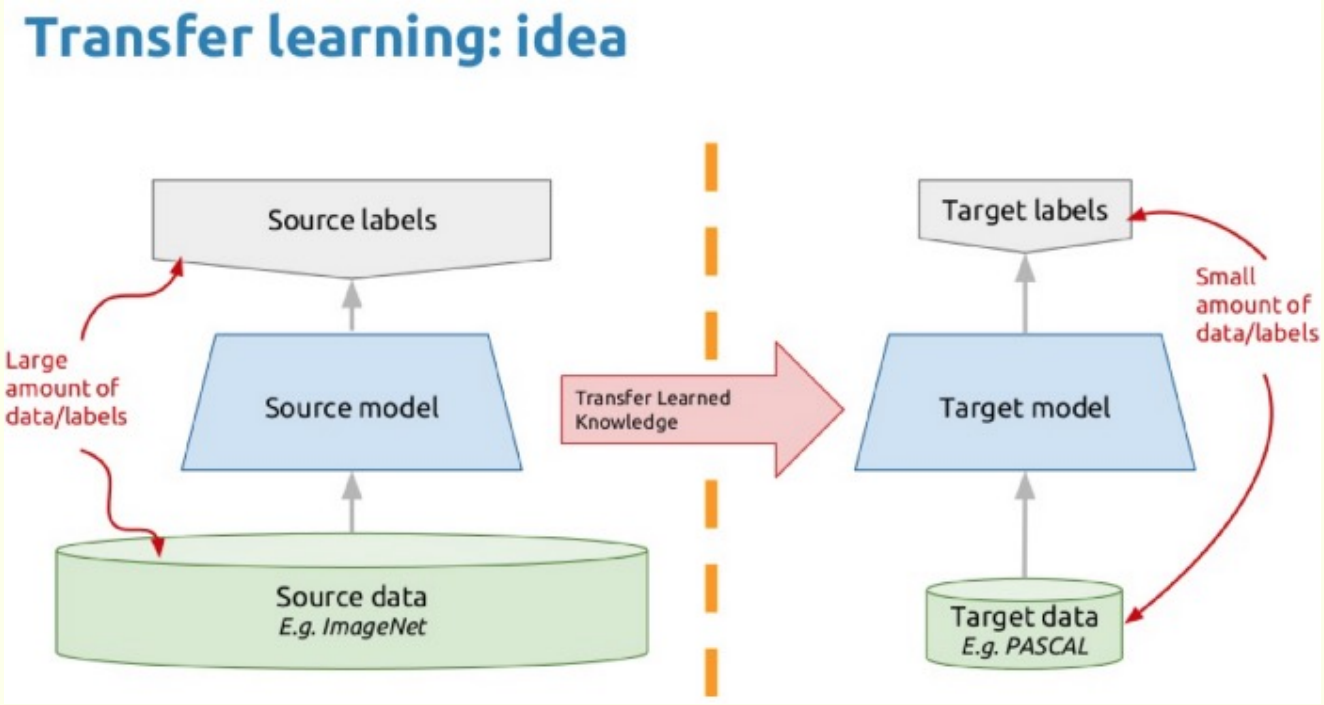
CNN Deep Learning Model



Visual Geometry Group VGG16

Model Training

Face Recognition Using Transfer Learning (Pre-Trained Model VGG16

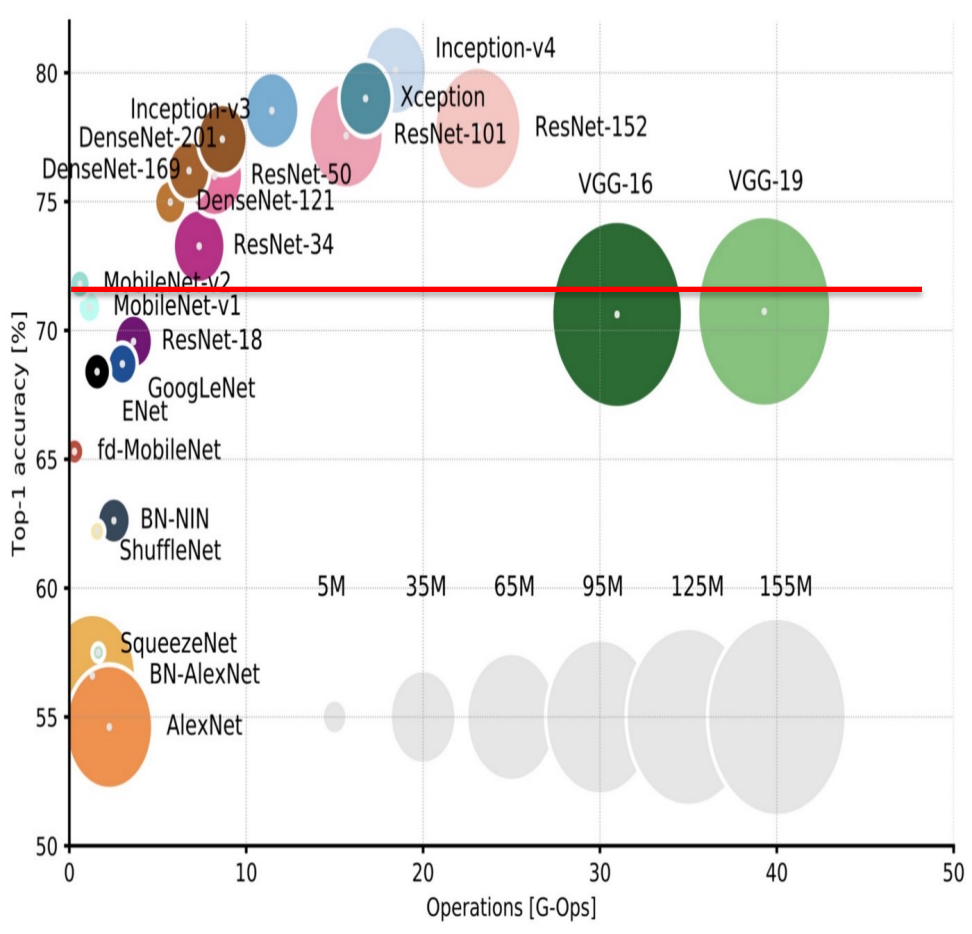


Transfer Learning

The knowledge of an already trained machine learning model is applied to a different but related problem

- Change input data – fecal image from chicken
- Change target labels – 4 classes(Cocci, healthy, ncd, Salmo)

Pre-trained model as Feature Extractor



Instead of building an image recognition algorithm from scratch, you can expedite the process by leveraging pre-trained models like Google's Inception model, which is trained on ImageNet data to identify images within pictures. One approach is to modify the pre-trained model by removing its final dense layer responsible for classification. By doing so, you effectively repurpose the model to serve as a feature extractor, preserving its ability to extract meaningful features from images. This approach is particularly useful when working with new datasets, such as in the context of developing a self-learning car. Instead of dedicating extensive time and resources to develop a new recognition algorithm, you can utilize the fixed feature extractor to streamline the process and focus on integrating these features into your car's learning framework

Visual Geometry Group, from the Oxford University have CNN architecture of model

VGG16

- **Large feature sizes** in many layers
- Inference was **quite costly at run-time**
- **Starter model** in transfer learning image classification
- **Easy to pre-processing** for training

04. Evaluated Model

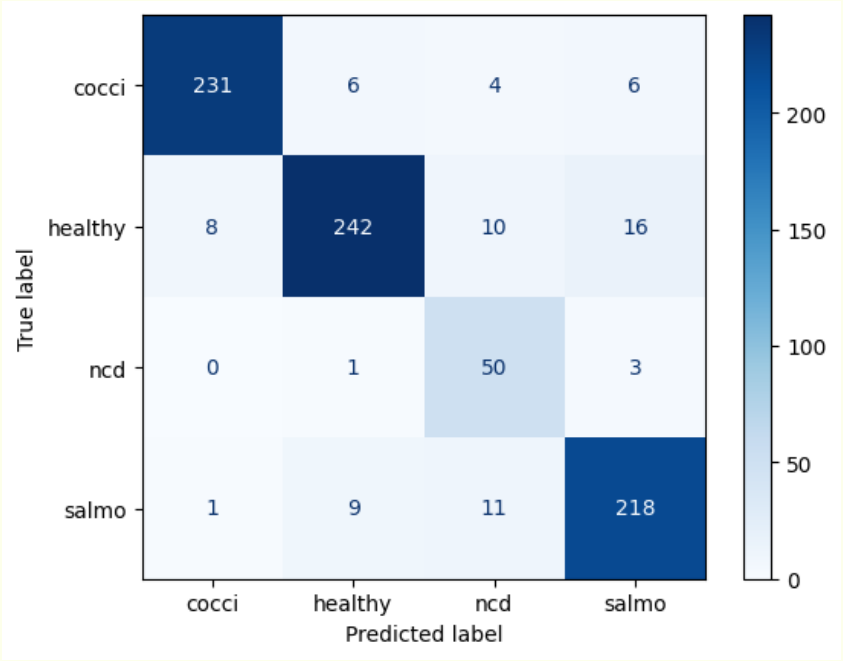
Parameter	CNN Baseline	VGG16 Transfer Learning	VGG16 Fine Tunning	Yolov8 Transfer Learning	Yolov8 Fine Tunning
Accuracy score training	0.95	0.82	0.99	0.98	0.99
Accuracy score validation	0.88	0.80	0.93	0.90	0.92
F1 score average	0.86	0.74	0.92	0.88	0.92
Size model(MB)	24.11	56.23	110.26	9.13	23.46
Number parameters	2 M	14 M	14 M	2 M	2M
Input image size	(128,128,3)	(224,224,3)	(224,224,3)	(128,128,3)	(128,128,3)

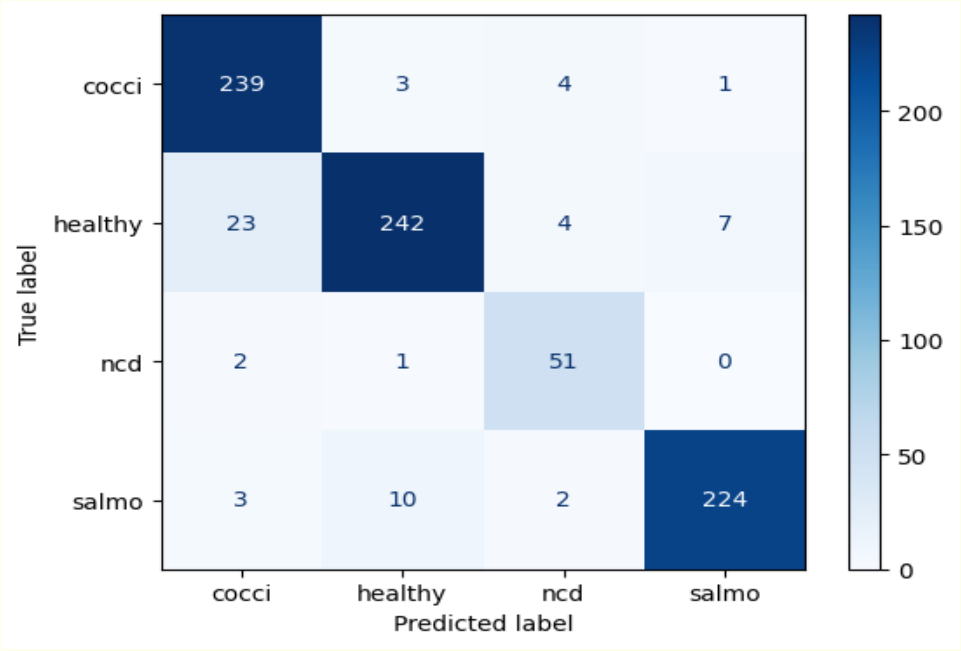
Parameter	Transfer Learning
Accuracy score training	0.98
Accuracy score testing	0.93
F1 score average testing	0.90
Size model(MB)	9.13
Number parameters	2 M
Input image size	(128, 128, 3)

The model achieves commendable performance, although there is a slight inclination towards overfitting that could be addressed. Its compact size renders it ideal for seamless integration into cloud-based platforms like Streamlit, facilitating easy uploading. The model's short run-time, attributed to its limited number of parameters, ensures swift processing, contributing to its efficiency. Furthermore, its robustness in handling images with small pixel inputs underscores its adaptability to diverse visual scenarios. In summary, the model's strong performance, compactness, rapid execution, and resilience to varying image inputs position it as a versatile and effective solution across different applications

Class	Precision	Recall	F1-score	No.picture
Cocci	0.95	0.96	0.95	232
Healthy	0.92	0.91	0.92	225
NCD	0.75	0.86	0.8	58
Salmo	0.95	0.92	0.94	290

“Future Technology with AI on Poultry Industry”


cocci
healthy
ncd
salmo
True label
231
6
4
6
8
242
10
16
0
1
50
3
1
9
11
218
cocci
healthy
ncd
salmo
Predicted label
200
150
100
50
0


cocci
healthy
ncd
salmo
True label
239
3
4
1
23
242
4
7
2
1
51
0
3
10
2
224
cocci
healthy
ncd
salmo
Predicted label
200
150
100
50
0

MODEL VERSION API KEY

Upload Method Select File

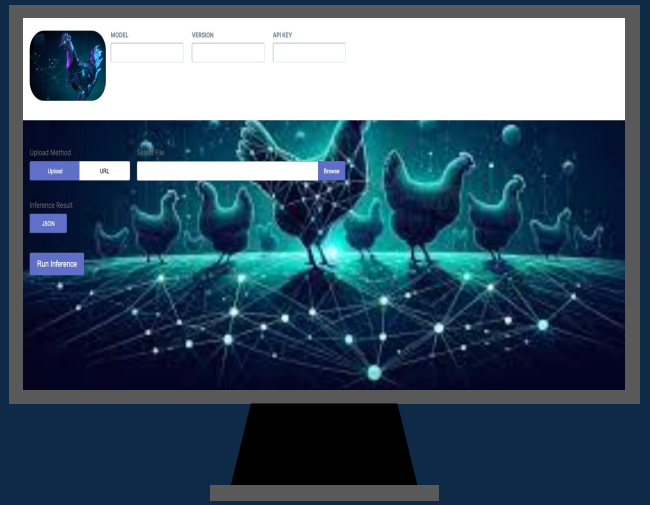
Upload URL Browse

Inference Result

JSON

Run Inference

WEB APP



THANK YOU
FOR YOUR ATTENTION

Thanks!

Does anyone have any questions?

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