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CHICKENME: CLASSIFICATION OF CHICKEN DISEASES FROM FECAL IMAGES

DEFENSE EXAM 2023

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CHICKEN ME

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ABOUT CHICKENME

Smart-farming technology for classification Of
Chicken Diseases From Fecal Images

- An automated system for disease classification that detects and predicts health conditions in chickens. The system achieves this by predicting images of chicken droppings, utilized object detection and deep learning technology.

- Implemented within the LINE OA platform for user-friendly access and real-time communication.

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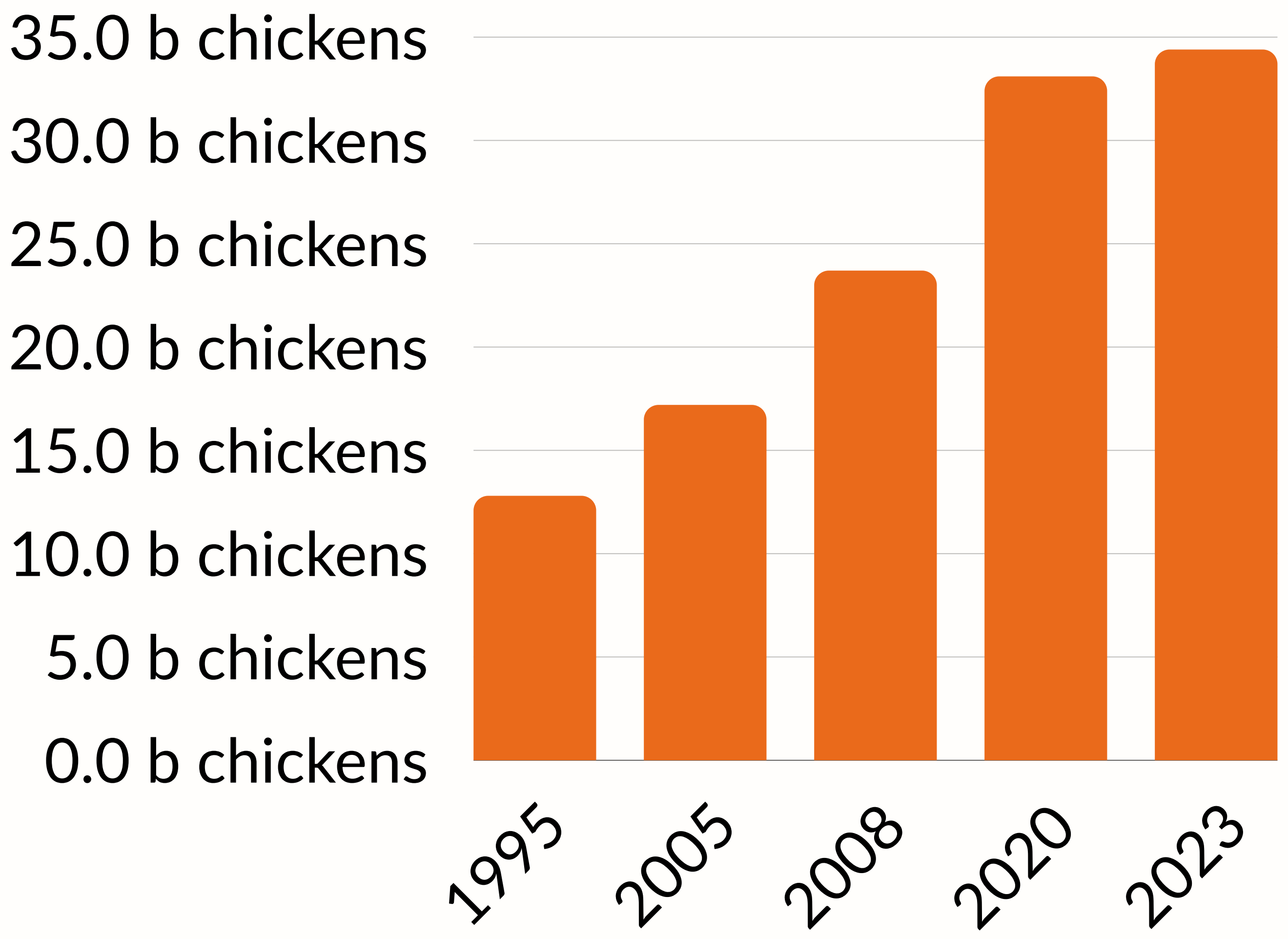
PROBLEM STATEMENTS

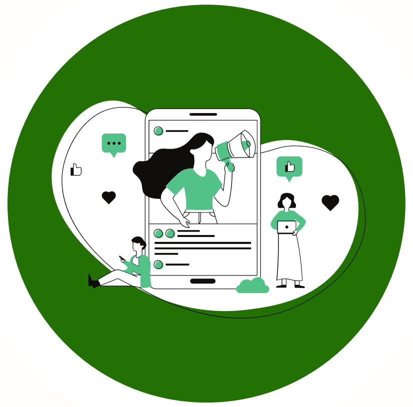


- **Approximately 34.4 billion chickens worldwide in 2023**
- There are many levels of standards for chicken livestocks
- Some diseases require high epidemic control; **high severity of the disease**
- Disease confirmation using **PCR can be costly.**

PROJECT OBJECTIVES

AUTOMATED DISEASE DETECTION

- Utilize Deep Learning to rapidly and accurately segment and detect diseases from chicken-dropping images.



DELIVER RESULT VIA THE LINE OA

- Implement deep learning within the Line OA
- User-friendly accessibility
- Time-saving experience

POULTRY DISEASES AND HEALTHY DROPPINGS CHARACTERISTICS

HEALTHY

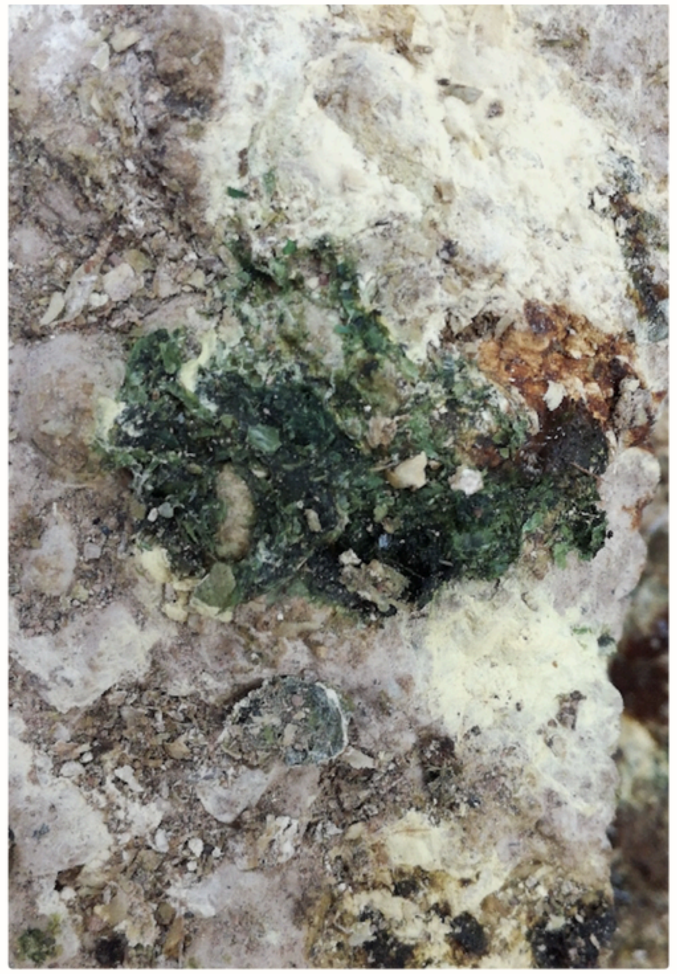
- Well-formed, solid
- various shades of brown.

COCCIDIOSIS

- Dark brown, flat feces,
- Diarrhea with blood or mucus
- It is a common disease

SALMONELLA

- White, loosely shaped
- It affects people's health and may cause infection



NEWCASTLE DISEASE (NCD)

- Solid green feces
- The highest level of seriousness can cause death

RELATED WORK

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RELATED WORK

DATASET

Machine Learning Dataset for Poultry Diseases Diagnostics

Machuve, Dina[1]; Nwankwo, Ezinne[2]; Mduma, Neema[1]; Mbelwa, Hope[1]; Maguo, Evarist[3]; Munisi, Charles[3]

Hide affiliations

1. Nelson Mandela African Institution of Science and Technology
2. Duke University
3. Elang'ata Agrovet Services

The annotated dataset of poultry disease diagnostics for small to medium-scale poultry farmers consists of poultry fecal images. The poultry fecal images were taken in Arusha and Kilimanjaro regions in Tanzania between September 2020 and February 2021 using Open Data Kit (ODK) app on mobile phones. The typical normal fecal material which is the 'healthy' class and Coccidiosis disease, the 'cocci' class were taken from poultry farms. The chickens were inoculated for Salmonella disease and fecal images taken from the diseased chickens for the 'salmo' class after one week. The chickens were also inoculated for Newcastle disease and fecal images for the 'ncd' class were taken within three days.

ALGORITHMS

Contents lists available at ScienceDirect

Smart Agricultural Technology

journal homepage: www.journals.elsevier.com/smart-agricultural-technology

ELSEVIER

Smartphone based detection and classification of poultry diseases from chicken fecal images using deep learning techniques

Mizanu Zelalem Degu[a,c,*], Gizeaddis Lamesgin Simegn[b,c]

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[c] *AI and Biomedical Imaging Research Unit, Jimma Institute of Technology, Jimma, Ethiopia*

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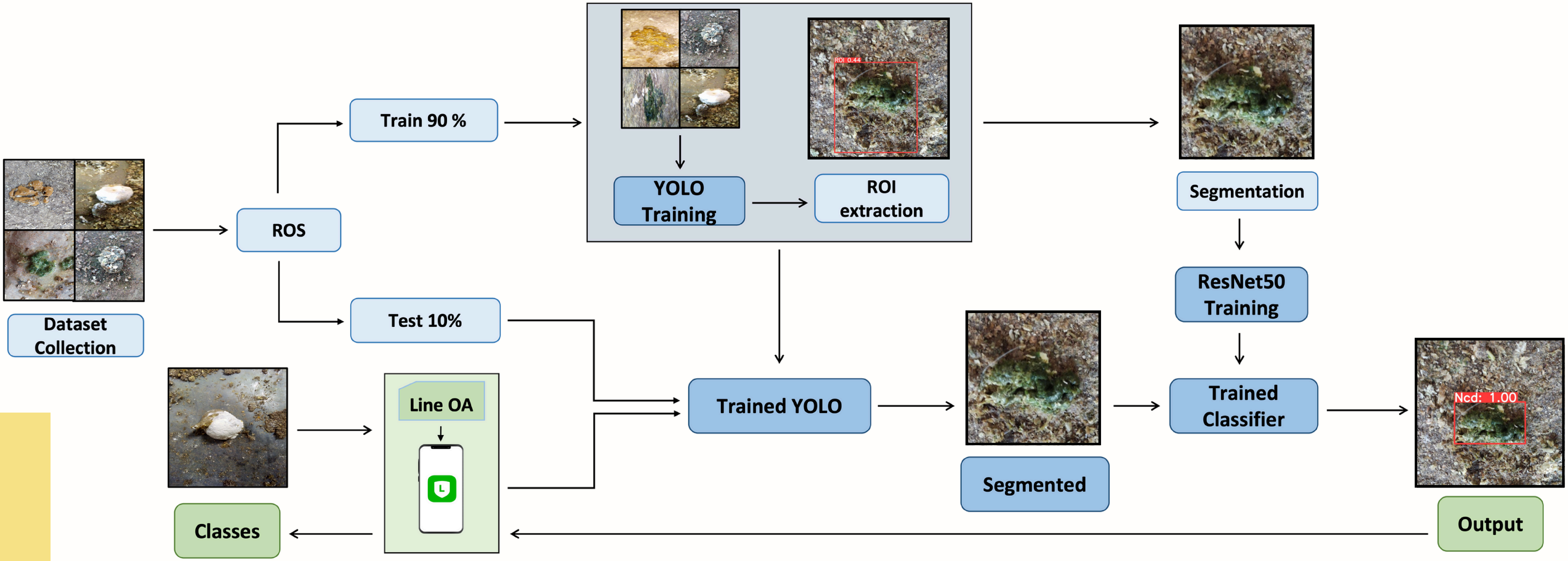
SYSTEM OVERVIEW



DATASET

Datasets —Tanzania→

Total Image - 8067
cocci - 2476
healthy - 2404
ncd - 562
salmo - 2625

Non-PCR - 6812
cocci - 2103
healthy - 2057
ncd - 376
salmo - 2276
imgObjDet_Yolo

PCR - 1255
pcrcocci - 373
pcrhealthy - 347
pcrncd - 349
pcrsalmo - 189

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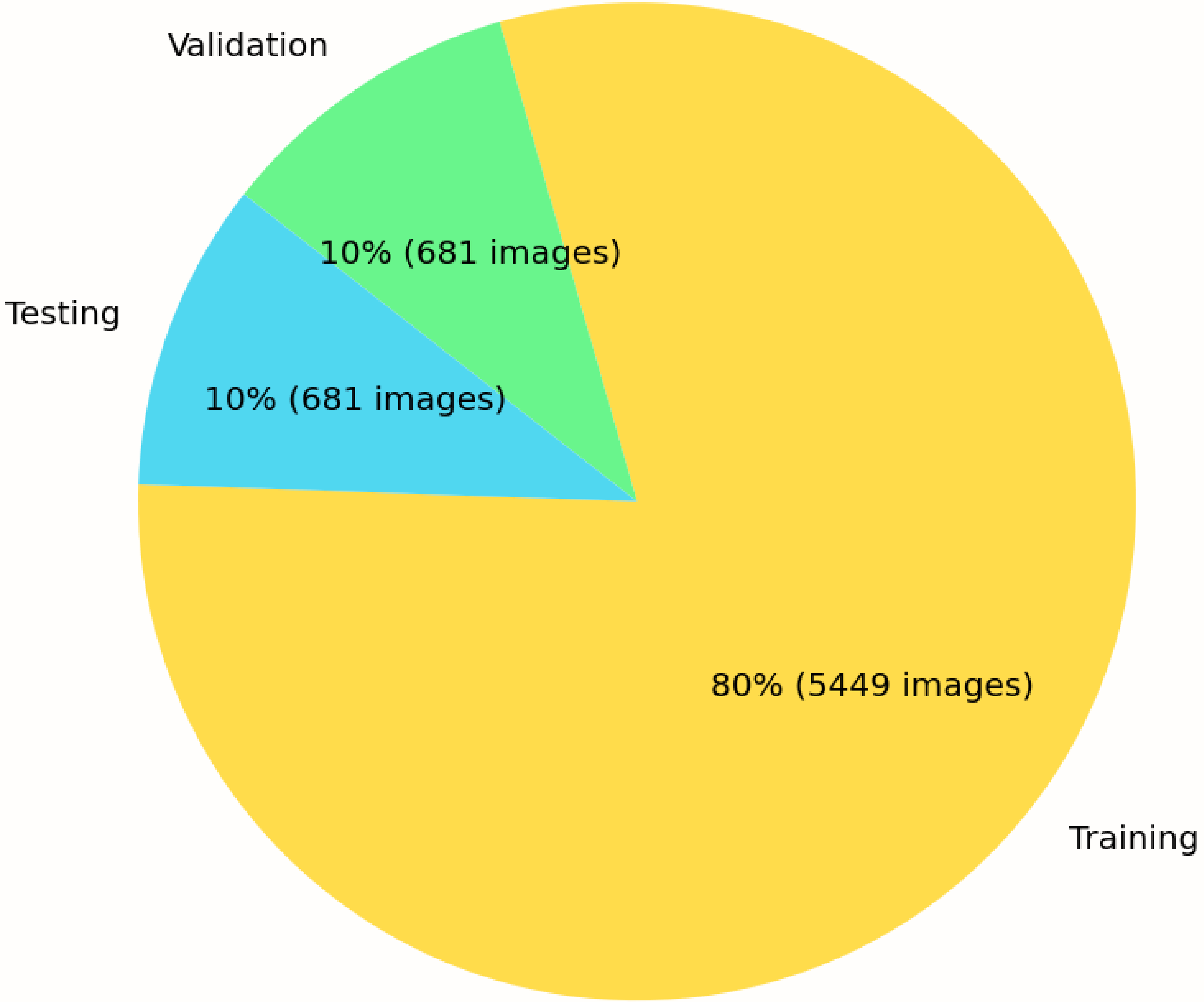
YOLO DATA SPLITTING



YOLO MODEL DEVELOPMENT

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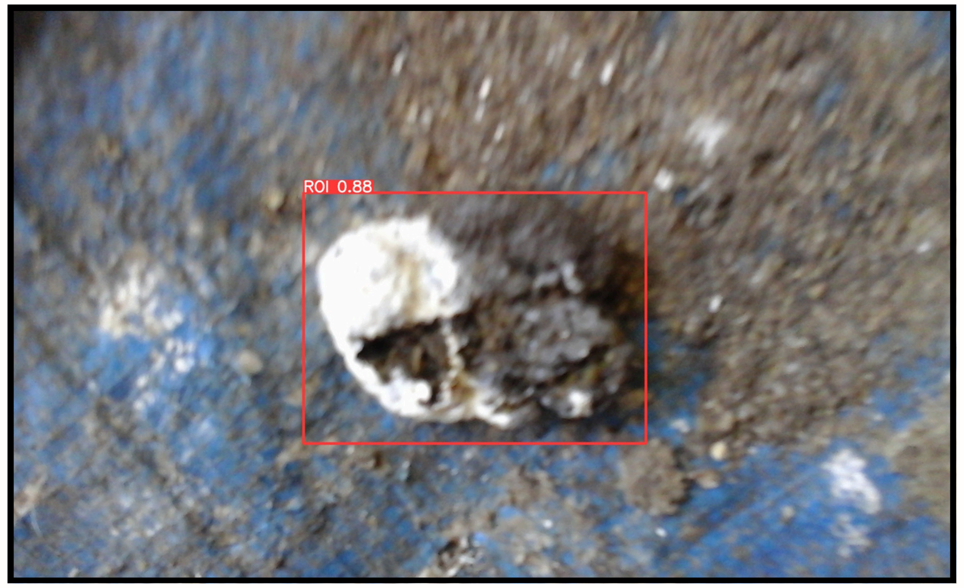
OBJECT DETECTION / ROI EXTRACTION

OBJECT DETECTION

- Detect and locate instances of objects in images or videos.
- Determining the position and boundaries of objects within an image.
- Indicates object positions and provides classification



REGION OF INTEREST (ROI) EXTRACTION

- Identifies and isolates specific areas within an image.
- Avoid the processing of irrelevent image points and accelerate the processing.
- Dividing the image into useful segments.

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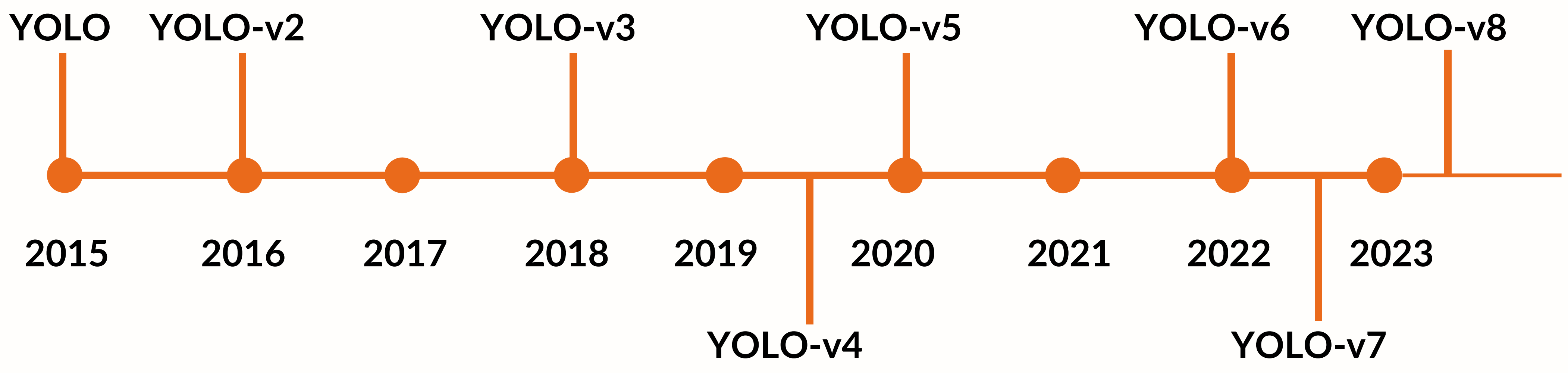
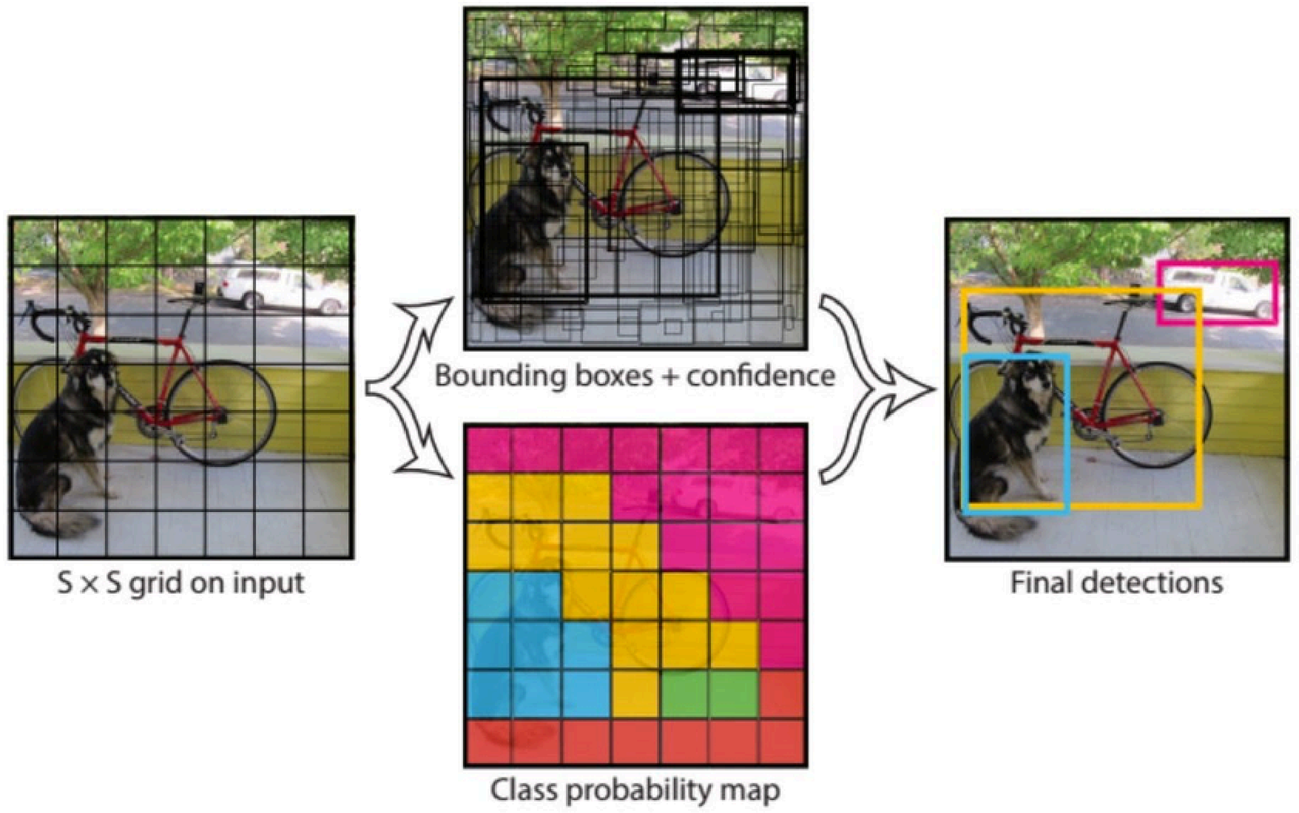
YOLO (YOU ONLY LOOK ONCE)

- The high ability to execute real-time object detection tasks.
- Leveraging CNNs for the detection and classification of objects in images.



YOLO ALGORITHM



- The image is divided into grid cells, each forecasting B bounding boxes with confidence scores.
- Grid cells predict class probabilities to determine the class of each object.

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DARKNET FRAMEWORK AND DARKNET53

DARKNET FRAMEWORK

- **Known for**: Association with the YOLO for real-time object detection.
- **Features**: Renowned for its simplicity and efficiency.

DARKNET53 ARCHITECTURE

- **Structure**: Consists of 53 layers.
- **Role**: Acts as the backbone or feature extractor in YOLOv3.
- **Attributes**: Lightweight and fast.
- **Usage**: Commonly pre-trained on ImageNet; used as a base for various visual tasks.

	Type	Filters	Size	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3 / 2	128 × 128
1×	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3 / 2	64 × 64
2×	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3 / 2	32 × 32
8×	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32
	Convolutional	512	3 × 3 / 2	16 × 16
8×	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3 / 2	8 × 8
4×	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Avgpool		Global	
	Connected		1000	
	Softmax			

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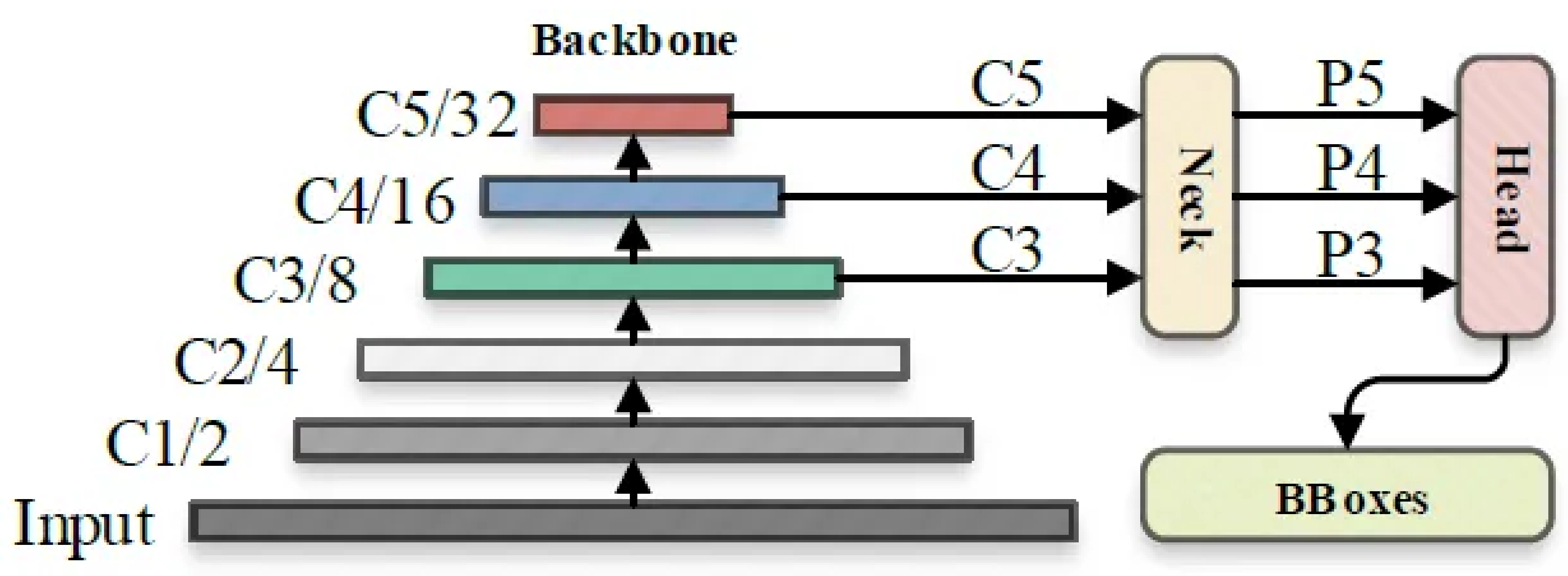
YOLO V5



- Backbone: Extracts features and creates lower-dimensional representations.
- Neck: Generate three feature maps P3, P4, and P5 (in the YOLOv5, the dimensions are expressed with the size of 80×80, 40×40, and 20×20) for detecting different scale targets.
- Head: Generates bounding boxes, object confidence scores, and class probabilities.

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THE DIFFERENCE BETWEEN YOLOV3 AND YOLOV5

EASE OF USE

YOLOv3

- Requires more manual setup
- less streamlined tooling thanV5

YOLOv5

- Easier to use, a simpler development environment.
- Designed with PyTorch, making it more accessible to a broader audience.
- Community support

MODEL SIZE

YOLOv3

- Larger and heavier
- Resource requirements due to its architecture
    - Complicate deployment

YOLOv5

- Lighter and more efficient
- various model sizes from small to extra-large
- easier to deploy on hardware with varying resource constraints.

YOLO DATA PREPARATION AND PRE-PROCESSING

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BOUNDING BOX

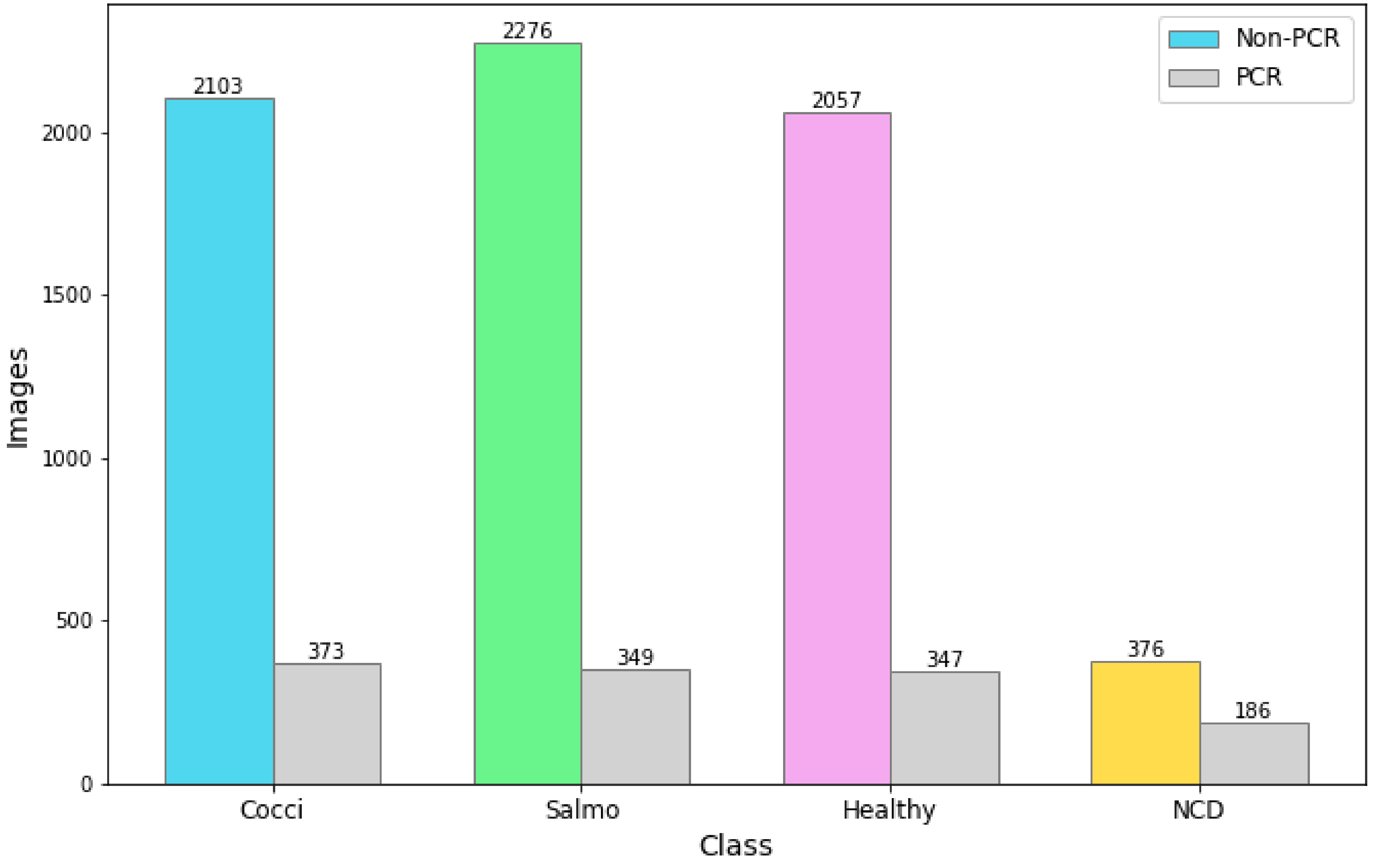
ROS (RANDOM OVERSAMPLING)

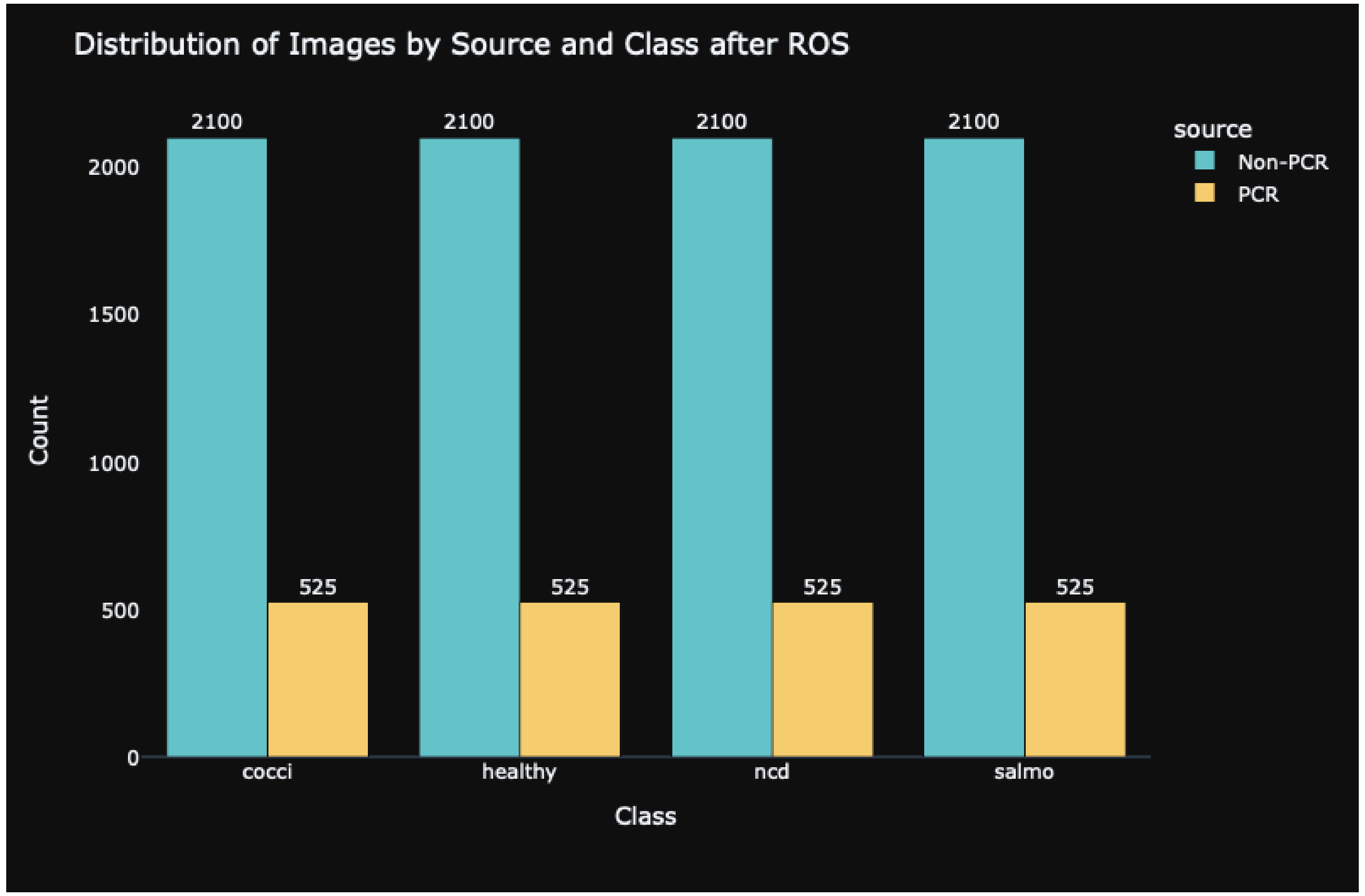
- A technique used to address class imbalance in datasets
- **How it works:** To make the number of samples in the minority class closer to or equal to the number of samples in the majority class.

BENEFITS:

- **Improved Model Training:** Helps models learn features from both minority and majority classes, reducing bias.
- **Reduced Overfitting:** Proper use of ROS oversampling can increase data diversity, mitigating overfitting risks.

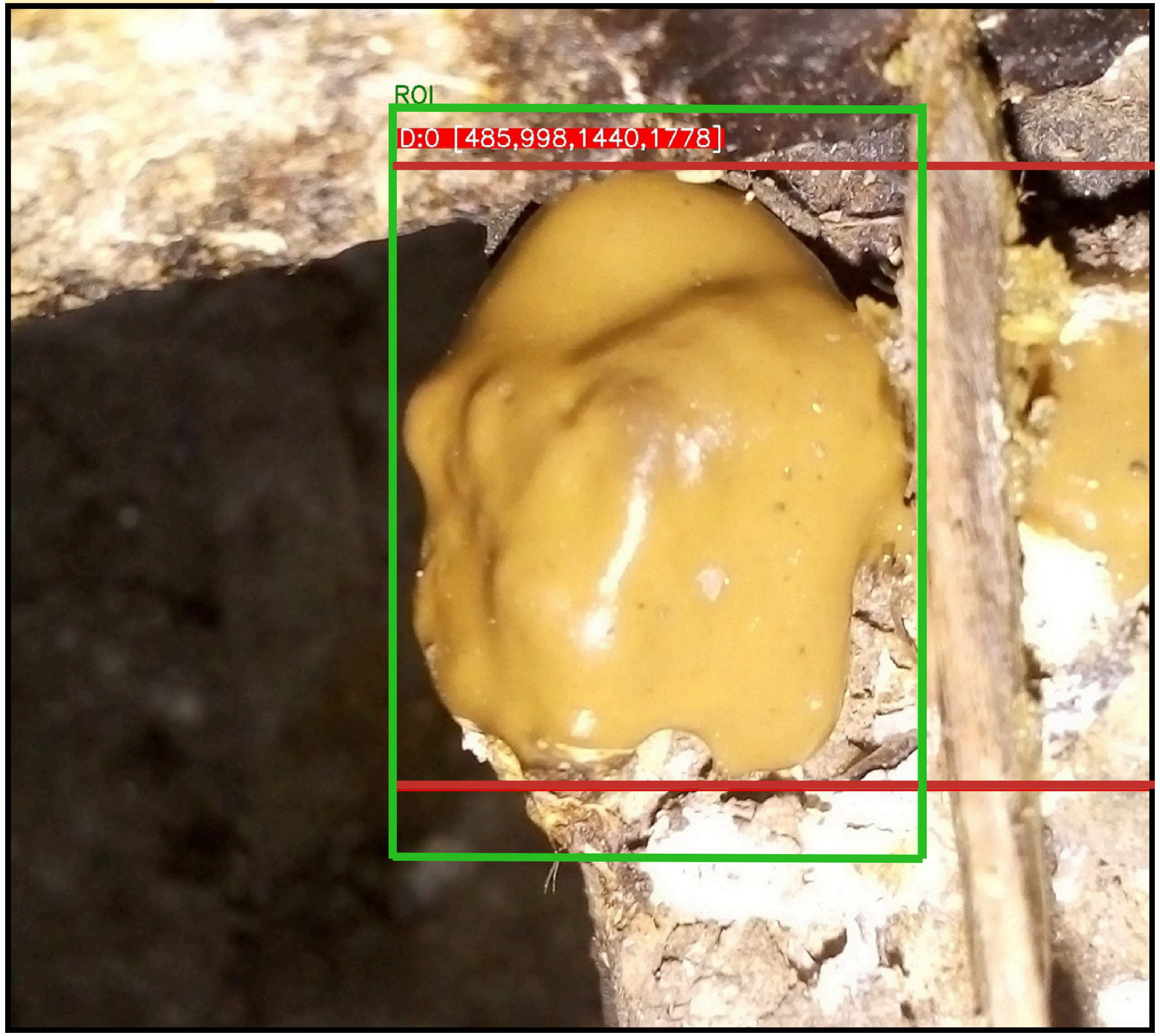
ROS (CONT.)


Non-PCR
PCR
2103
373
2276
349
2057
347
376
186
2000
1500
1000
500
0
Images
Cocci
Salmo
Healthy
NCD
Class


Distribution of Images by Source and Class after ROS
source
Non-PCR
PCR
2100
525
2100
525
2100
525
2100
525
2000
1500
1000
500
0
Count
cocci
healthy
ncd
salmo
Class

YOLO TRAINING AND TESTING PROCESS

YOLO MODEL OUTPUT



EXAMPLE OF INTERSECTION OVER UNION (IOU)

MODEL EVALUATION

MEAN AVERAGE PRECISION (mAP)

- Metric for evaluating object detection models.
- Indicates how well the model detects objects at various confidence levels.

- **INTERSECTION OVER UNION (IOU)**
    - Assesses the overlap between predicted and ground truth bounding boxes.
        - 1 = perfect overlap
        - 0 = no overlap.

Calculate Detection Scores

- Determine detection scores for each image in the dataset.

Compute Error Scores

- 1 - detection score = error score for each image.

Compute the Mean and Standard Deviation of IOU

- average (mean) and standard deviation

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YOLOV3 AND YOLOV5 EXPERIMENTS

Dataset	Architecture	Performance on Testing Data
		Mean Average Precision (mAP)
456 YOLO-labelled images with full size.	YoloV3	75.31 %
	Yolov5	**82.06 %**
6812 YOLO-labelled images with full size.	YoloV3	82.13 %
	Yolov5	**87.10 %**

Training Data

- Both were trained on a dataset of 6812 labeled full-size images from Tanzania, with identical hyper-parameters.

Testing Data

- Tested with 682 unlabeled images, with identical settings and hyper-parameters.

RESNET50

MODEL DEVELOPMENT

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RESNET50 MODEL : SEGMENTATION FROM YOLOV5

segmented YOLO for RESNET training

- YOLOv5 segments ROI from fecal images after successful training.
- Further processing.
- To extract relevant features from segmented ROI images.
- Learning hierarchical representations of spatial and textural image features.
- uses 10,500 segmented images from YOLOv5, resized to meet its input specifications.

IMAGE CLASSIFICATION

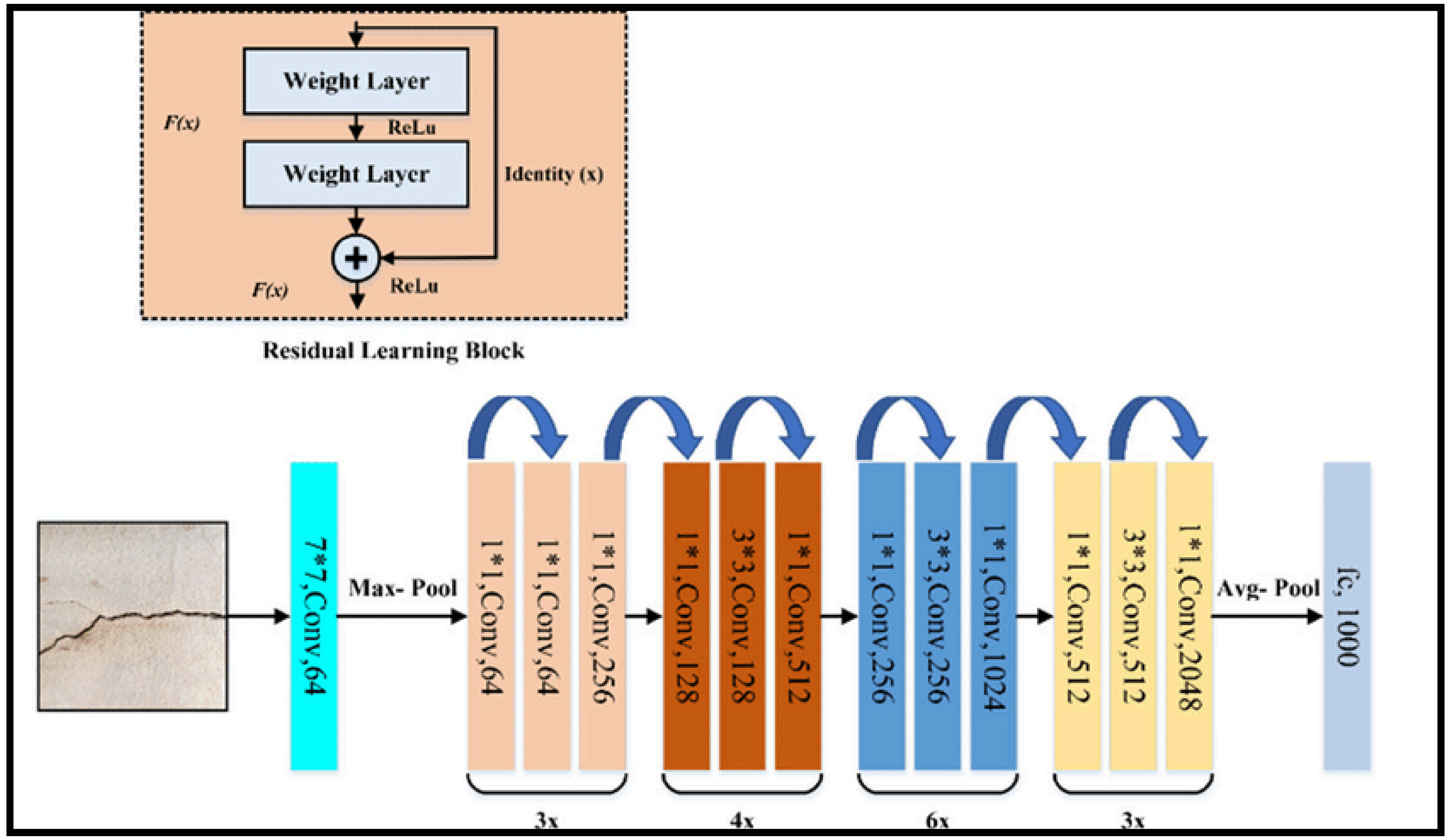
CONCEPT

- involves classify an image into predefined classes or labels.
- Categorize an input image by assigning it a specific label or class based on its content.

PROCESS

- Training a Model on a labeled dataset.
- Learns patterns and features that relate to each class.

RESNET50 MODEL FOR IMAGE CLASSIFICATION



OVERVIEW OF RESNET50

- A deep convolutional neural network with 50 layers.
- Designed for efficient training of deep networks.
- Widely used in various domains including facial recognition and autonomous vehicles.

KEY FEATURES OF RESNET50

- Architecture: 5 stages with convolutional and identity blocks, batch normalization, and ReLU activations.
- Skip Connections: Help bypass layers during forward pass to alleviate the vanishing gradient problem.
- Residual Learning: Focuses on learning the residual differences between input and output.

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RESNET50 TRAINING AND TESTING PROCESS

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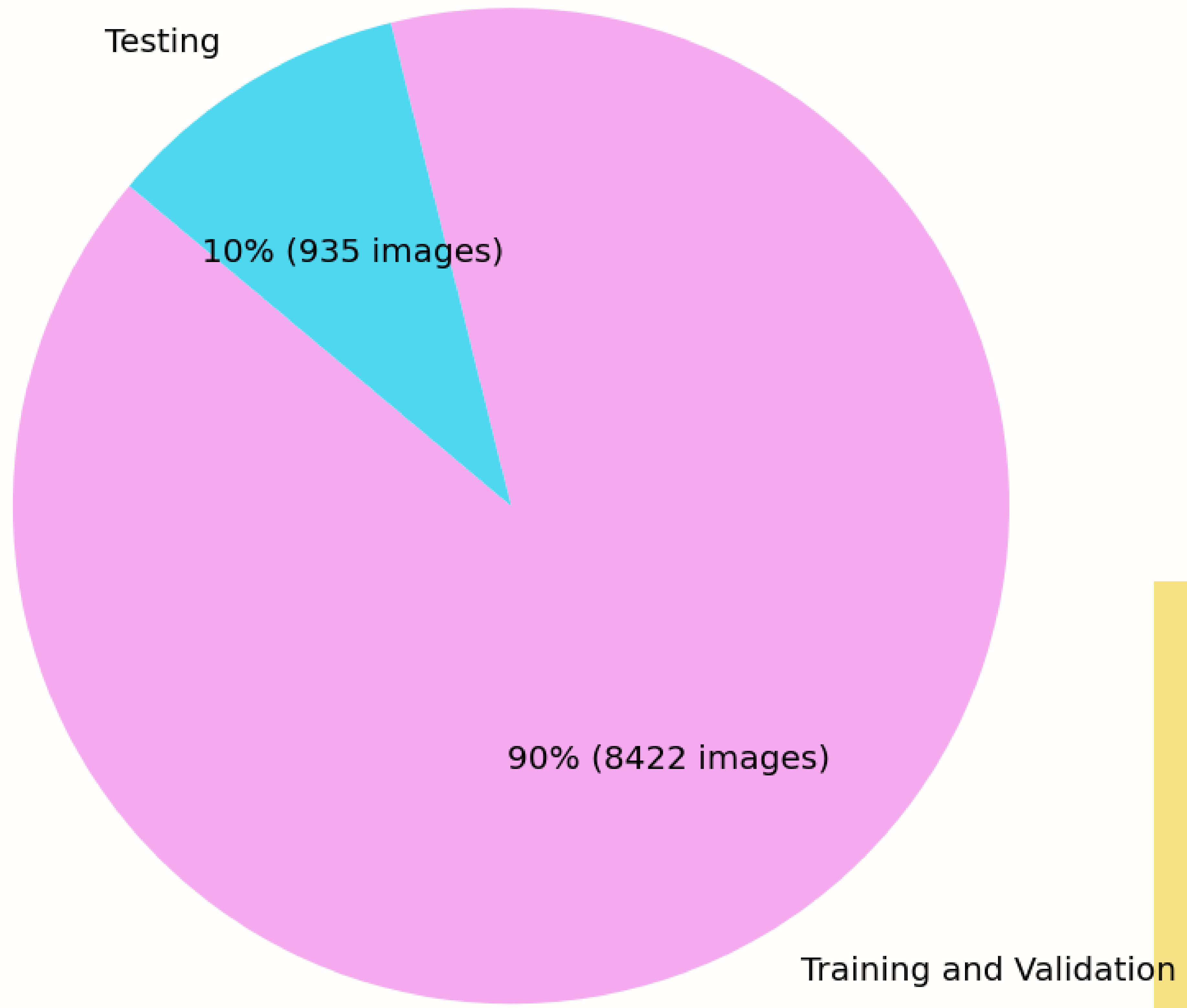
RESNET DATA SPLITTING

- 9385 segmented images as 90% for Final Training and Validation
- 936 segmented images as 10% for Final Model Testing

- Validation Data for 10-fold cross-validation
  - 90% is 8422 images
  - 10% is 842 images for Validating in each fold



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10-FOLD CROSS-VALIDATION

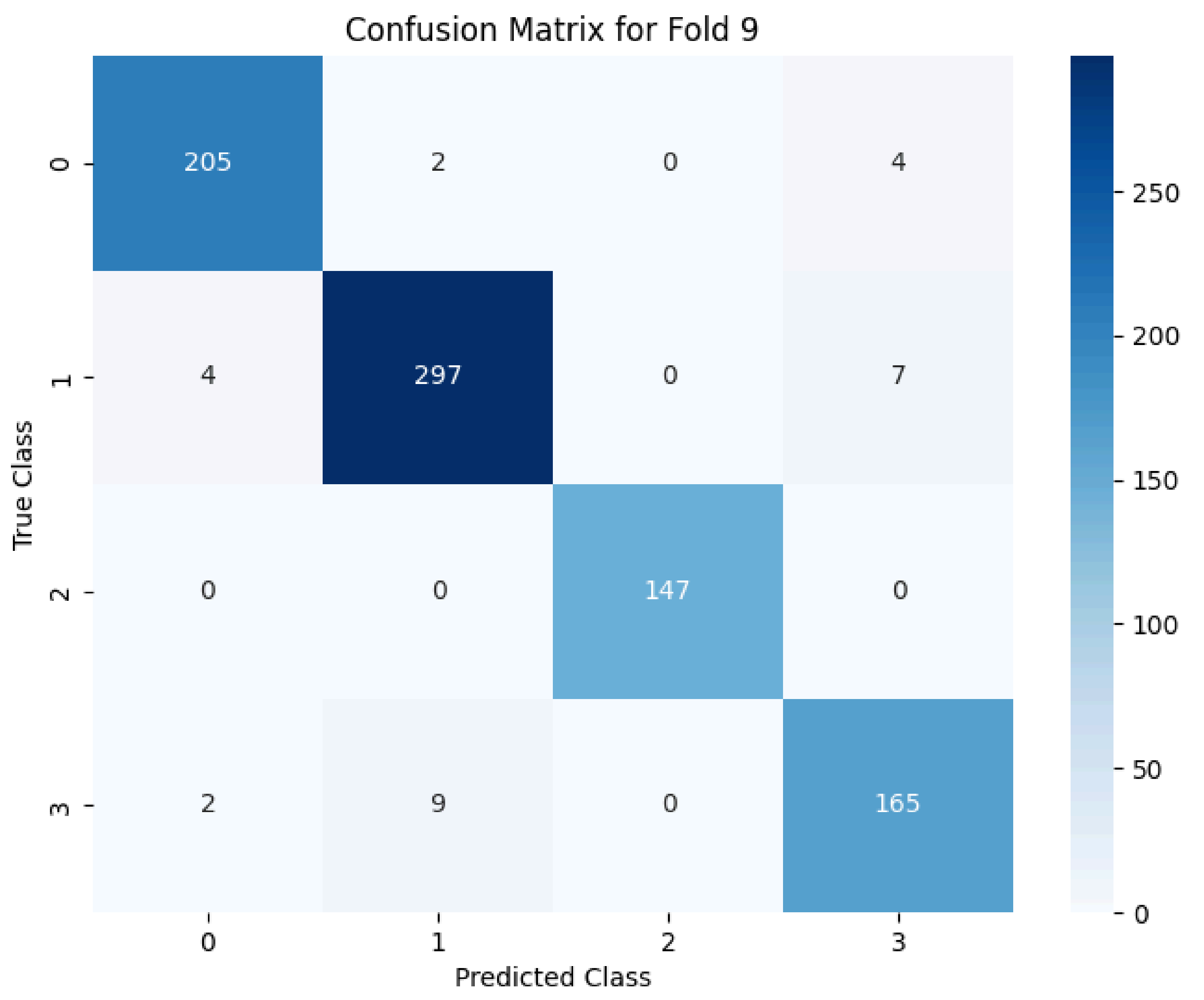
- A technique to evaluate model performance
- Dividing the dataset into ten equally sized subsets, known as **'folds'**
- **Trained and evaluated ten times**, with a different fold used as the validation set in each iteration.
- The remaining **nine folds** are used as **training data** for each iteration.
- Aggregated performance metrics from each fold assess the model's generalization ability.

10-FOLD CROSS-VALIDATION (CONT.)

```
Fold 9:
Number of Images: 842
Correct Predictions: 814
Incorrect Predictions: 28
Accuracy: 0.967
Confusion Matrix:
[[205   2   0   4]
 [  4 297   0   7]
 [  0   0 147   0]
 [  2   9   0 165]]
Classification Report:
              precision    recall  f1-score   support

           0       0.97      0.97      0.97       211
           1       0.96      0.96      0.96       308
           2       1.00      1.00      1.00       147
           3       0.94      0.94      0.94       176

    accuracy                           0.97       842
   macro avg       0.97      0.97      0.97       842
weighted avg       0.97      0.97      0.97       842
```



EXAMPLE OF 10-FOLD CROSS-VALIDATION CALCULATION

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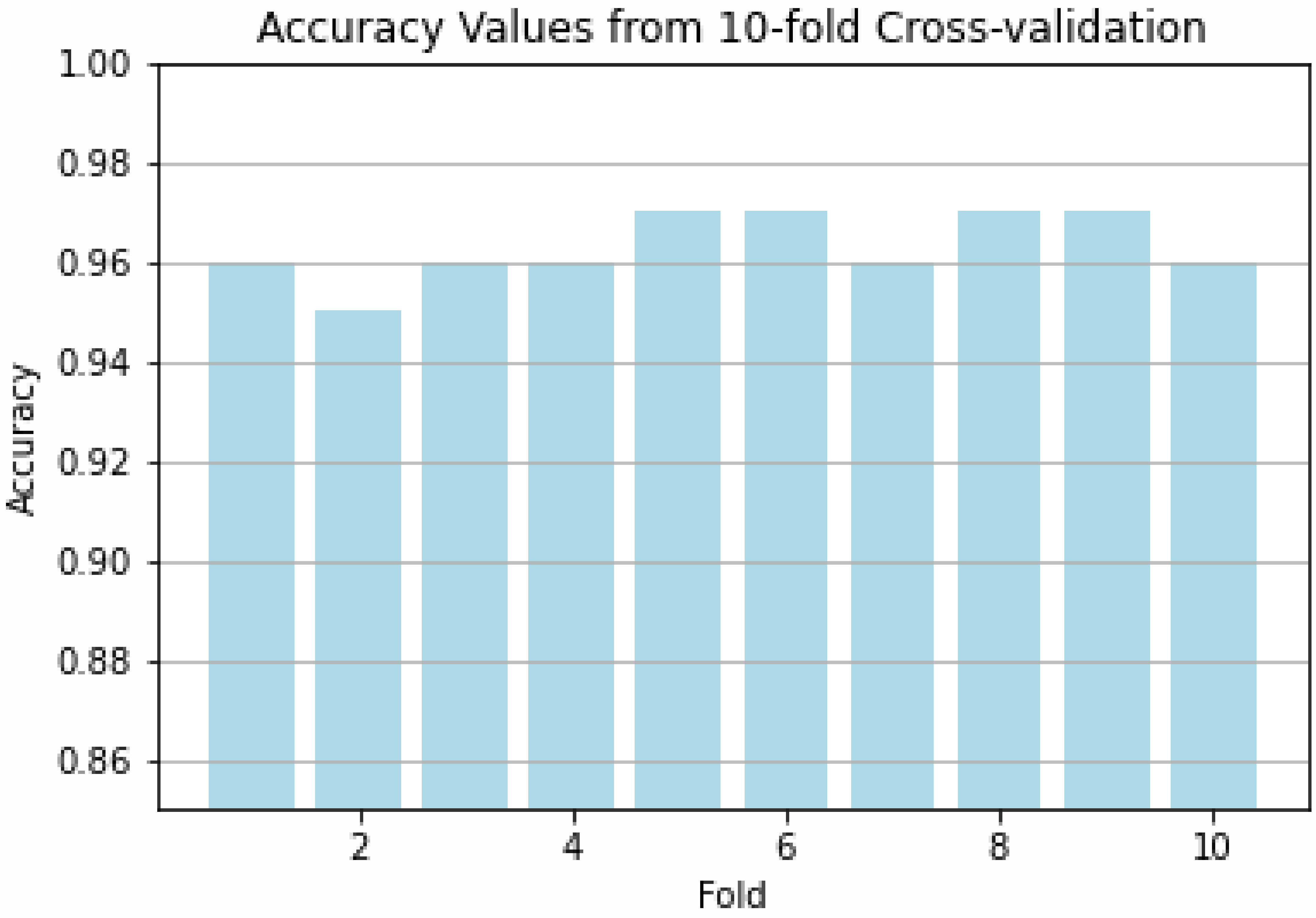
10-FOLD CROSS-VALIDATION (CONT.)



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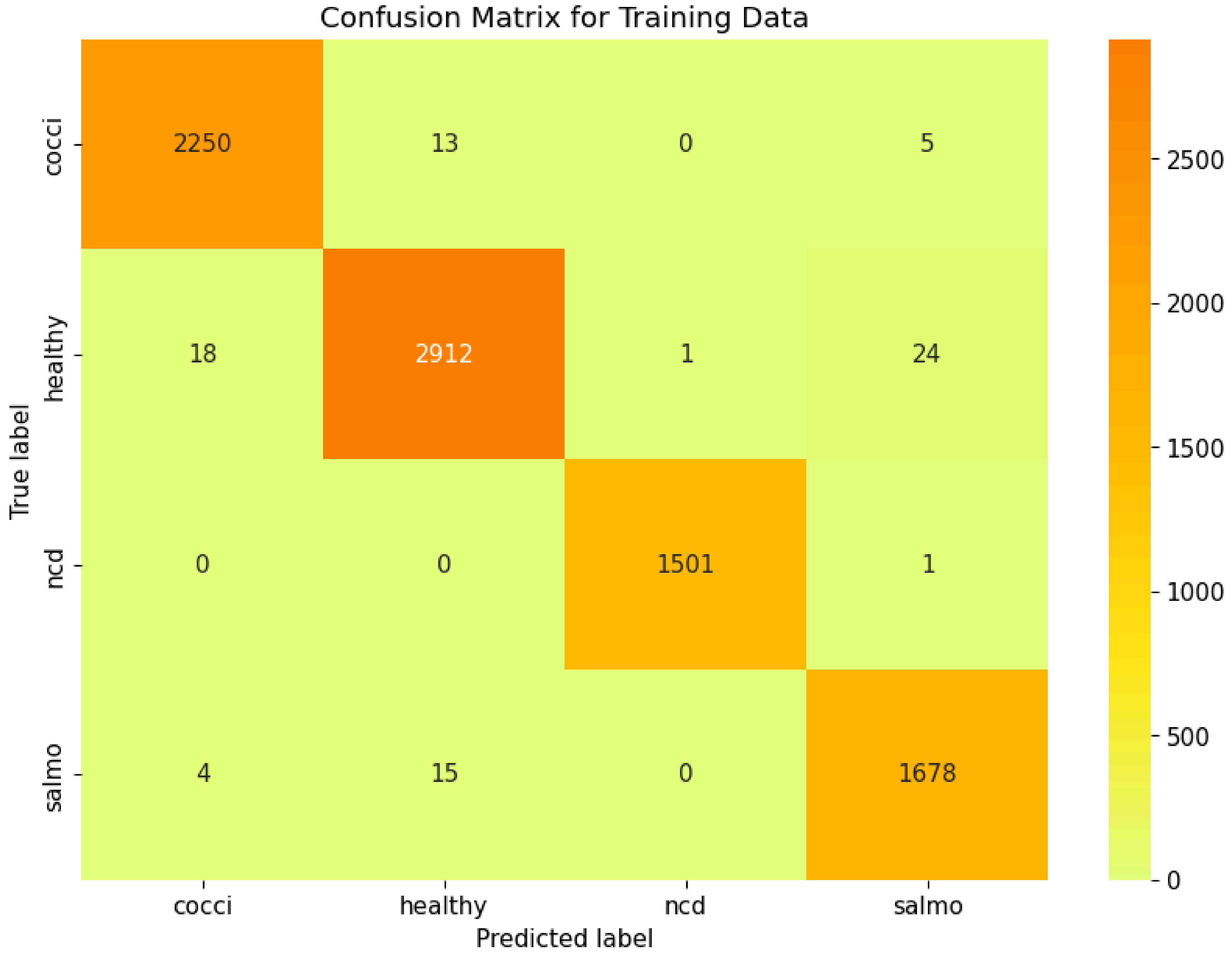
FINAL MODEL TRAINING



THE ACCURACY OF THE MODEL ON THE TRAINING DATA: 0.99

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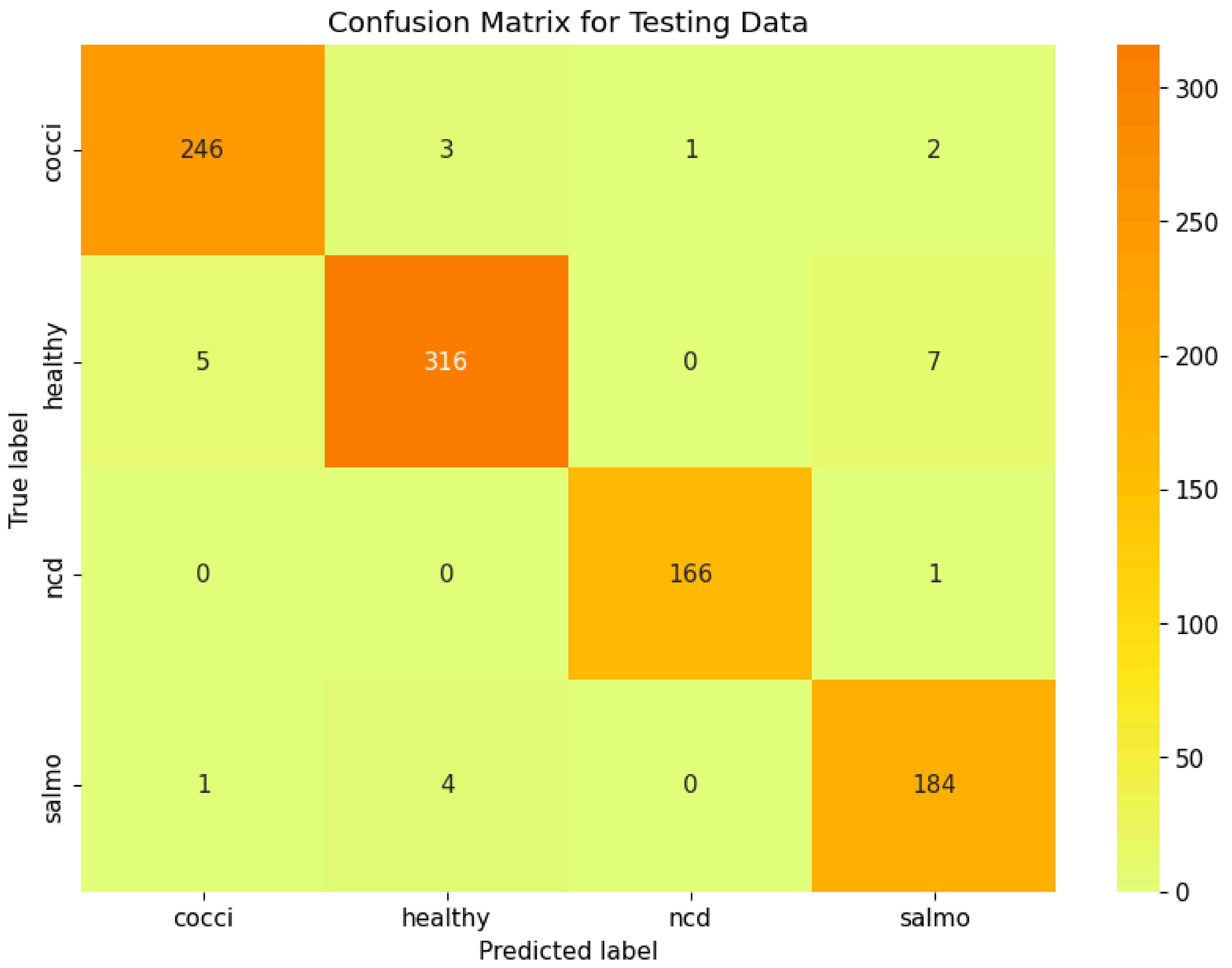
FINAL MODEL TESTING



THE ACCURACY OF THE MODEL ON THE TESTING DATA: 0.97

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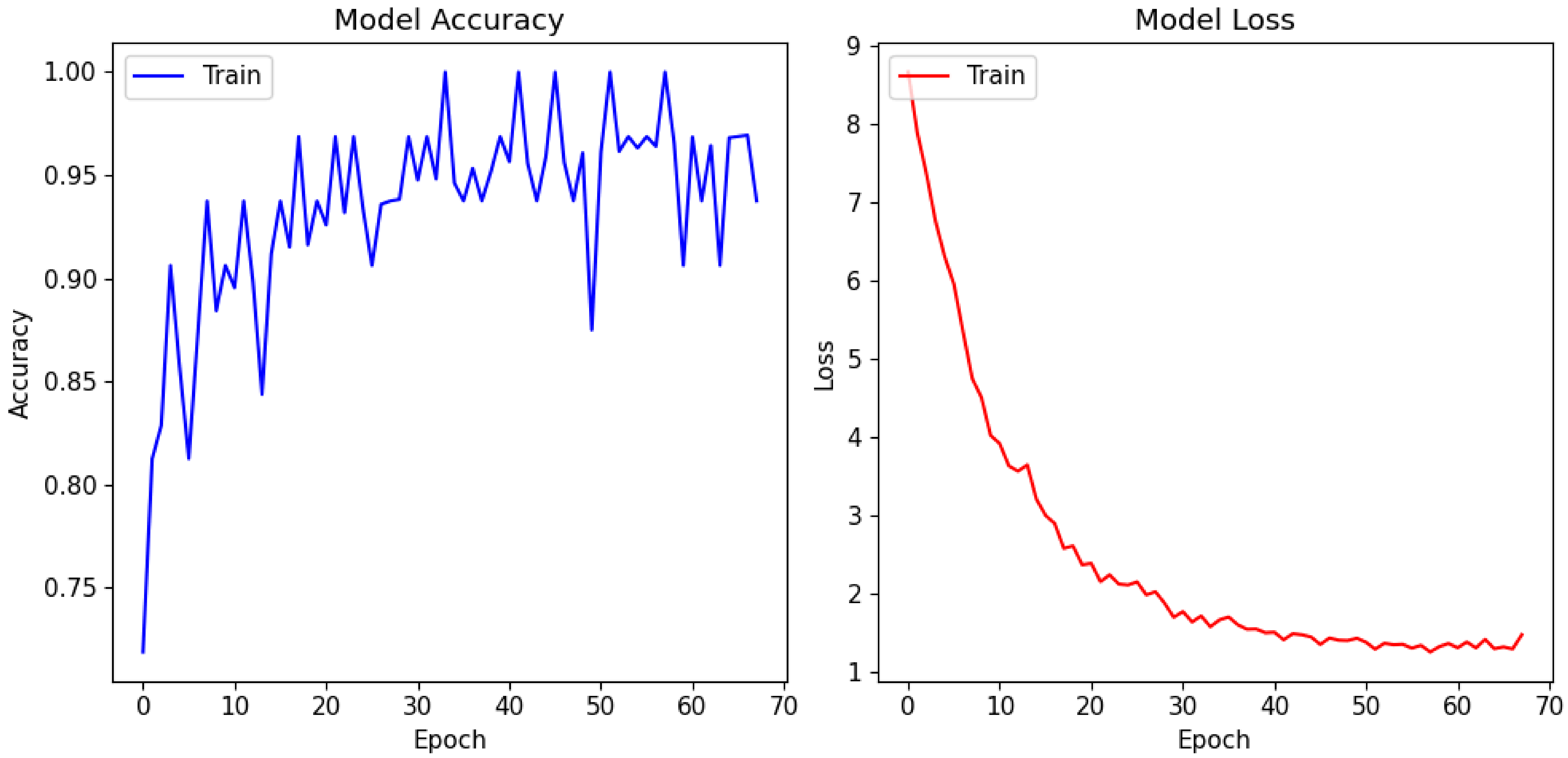
RESNET50 EXPERIMENT RESULT (CONT.)



The designed ResNet50 model was trained on a dataset of labeled images using a 90/10 train-test split ratio over 100 epochs, achieving an accuracy of 99%.

THAI DATASET

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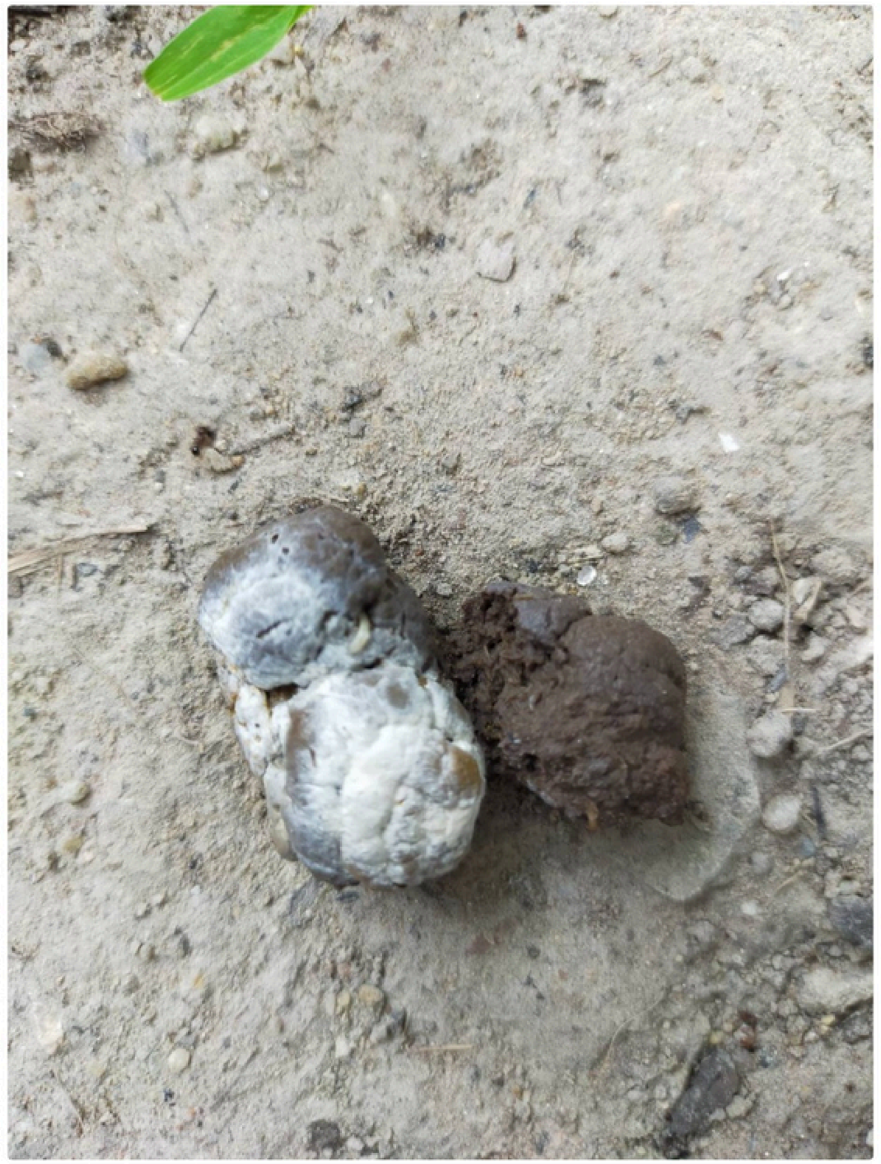
THAI CHICKEN FECES IMAGES DATASET



- Chang Khwang, Kanchanadit District, Surat Thani Province, Thailand
- 561 chicken feces images, captured via a mobile phone camera by local poultry farmers in March 2024.

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EXPERIMENT WITH THAI CHICKEN FECES IMAGES

- Confirm with the farm owner that the Thai chicken is in good health.

IMPLEMENTATION WITH LINE OA

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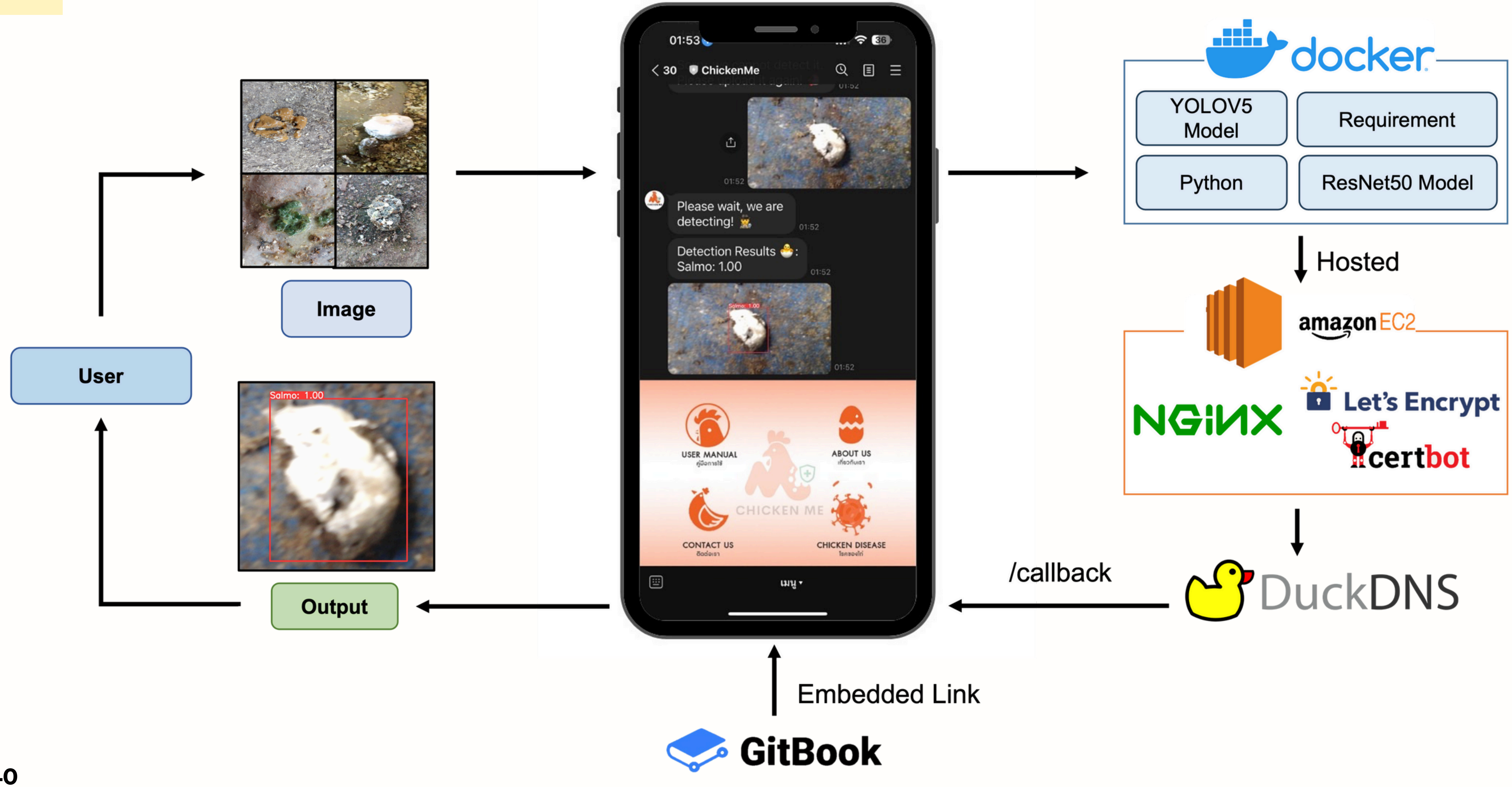
IMPLEMENTATION WITH LINE OA



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IMPLEMENTATION WITH LINE (CONT.)

```
FROM python:3.10.13-slim

WORKDIR /app

RUN apt-get update && apt-get install -y \
    ffmpeg \
    libsm6 \
    libxext6 \
    && apt-get clean && rm -rf /var/lib/apt/lists/*

COPY requirements.txt .
RUN pip install --no-cache-dir -r requirements.txt

COPY . .

ENV YOLO_CONFIG_DIR=/tmp/yolo
ENV MPLCONFIGDIR=/tmp/matplotlib

RUN echo "Make sure Torch and Flask are installed:" && \
    python -c "import flask" && \
    python -c "import torch"
CMD ["gunicorn", "line_up_fix:app", "--bind", "0.0.0.0:8000", "--workers", "1", "--timeout", "240"]

EXPOSE 8000
```

Dockerfile

docker

YOLOV5 Model

Requirement

Python

ResNet50 Model

Docker Image

```
Flask==3.0.2
gunicorn==21.2.0
line-bot-sdk==3.9.0
tensorflow==2.16.1
torch==2.2.0
yolov5==7.0.13
numpy==1.26.4
```

Image

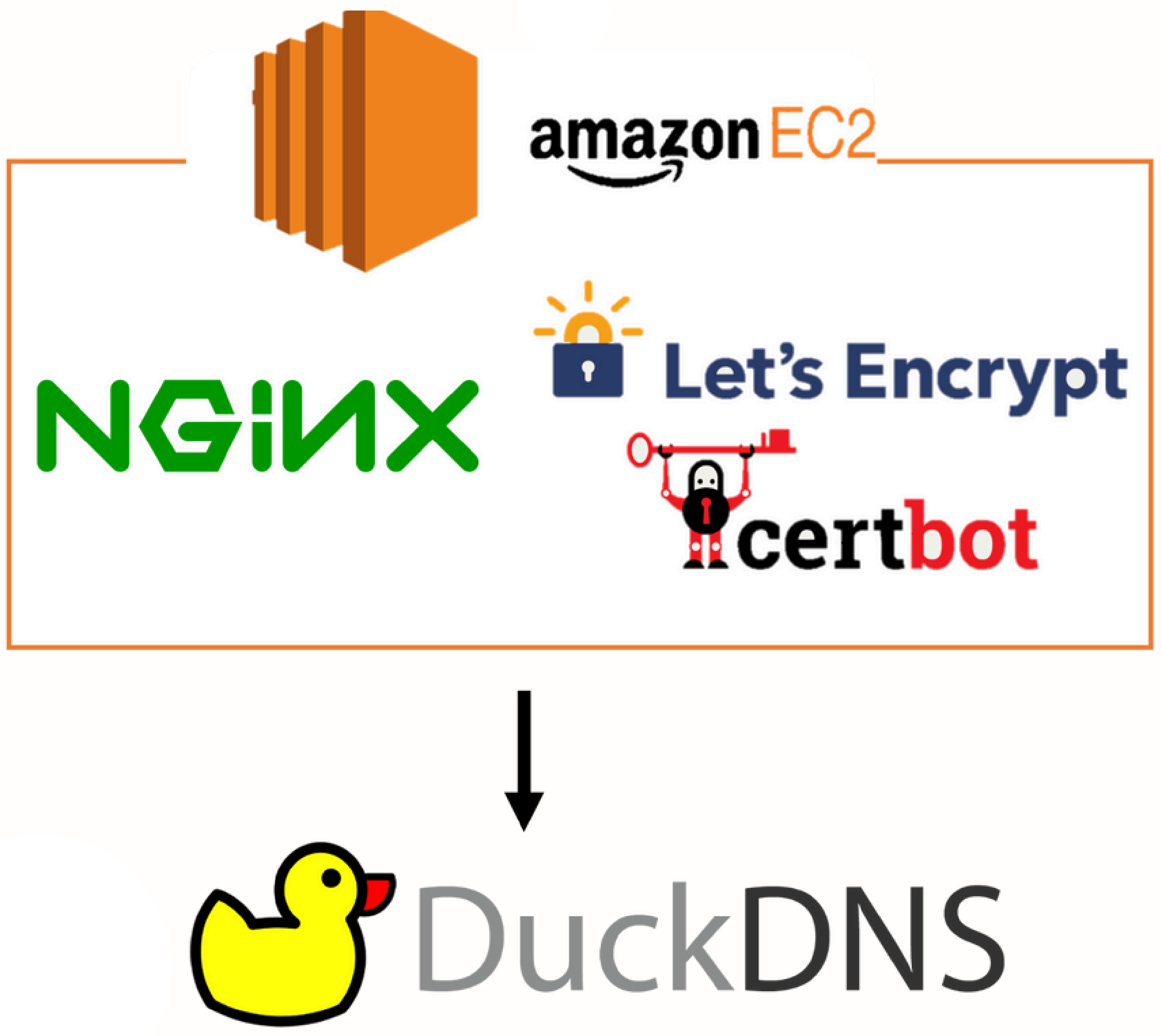
Flask

Start server → LineAPI → Load Model: YOLOV5 Model, ResNet50 Model

Object Detection

Classification

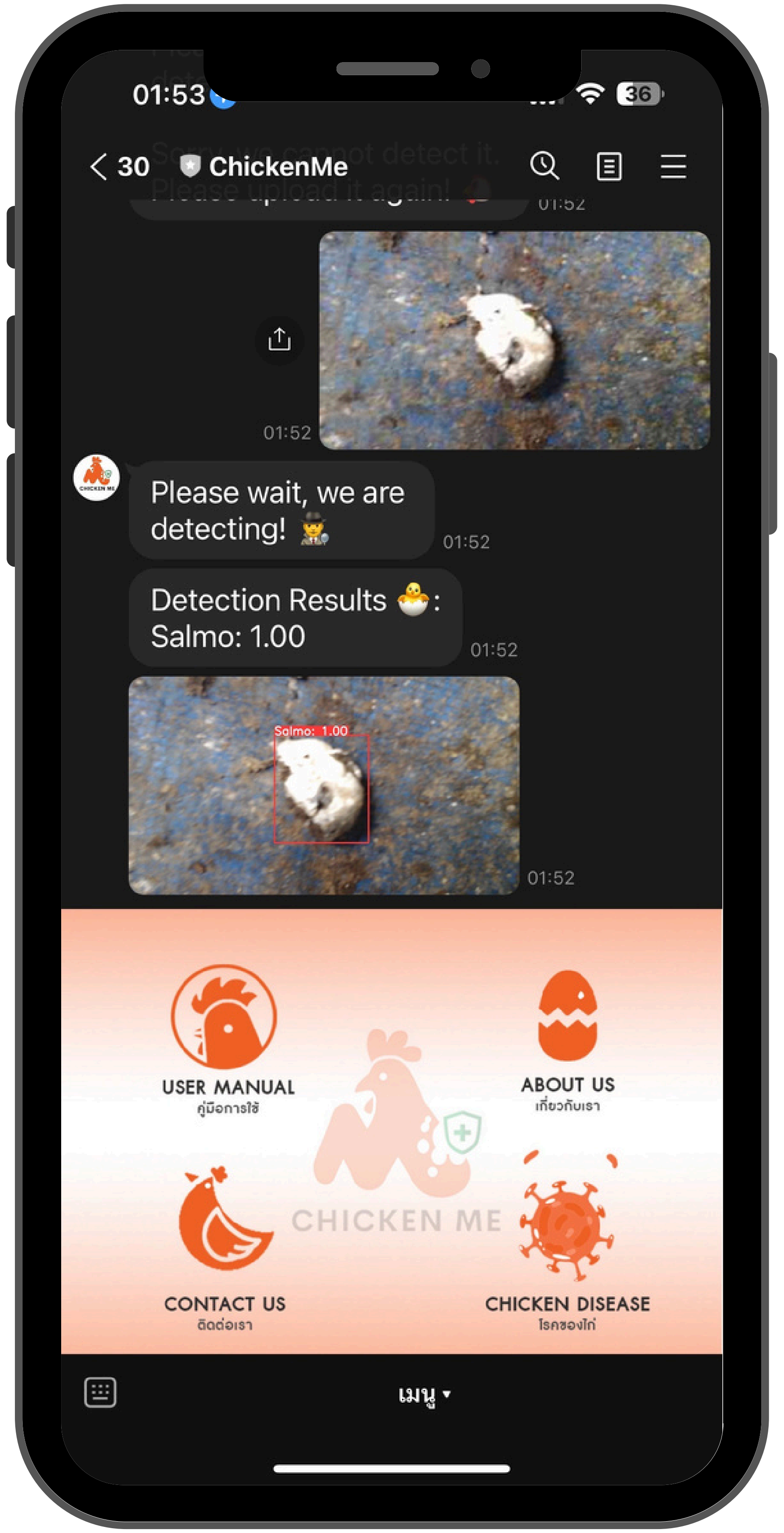
IMPLEMENTATION WITH LINE (CONT.)



Nginx Configuration for “chickenme.duckdns.org“

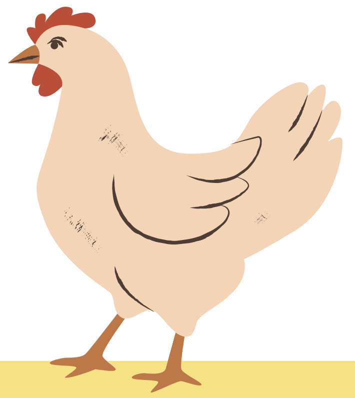
- HTTPS Configuration:
  - Port: 443 (SSL enabled)
  - SSL Certificates: Managed by Certbot (Auto-renewable from Let's Encrypt)
  - Proxy to Application: Requests are forwarded to an app running on localhost port 8000.
  - Header Settings: Pass client IP and protocol details to the backend for accurate request handling.
- HTTP to HTTPS Redirection:
  - Port: 80 (Standard for HTTP)
  - Behavior: All HTTP traffic is permanently redirected to HTTPS, ensuring secure connections.

ChickenME LINE ACCOUNT



RICH MENU

- **User Manual:** User guidance on how to use the ChickenME LINE account
- **About Us:** Information about the project and team.
- **Contact Us:** For users who want to inquire or ask for support
- **Chicken Disease Information:** To help users gain a better understanding of diseases in chicken.



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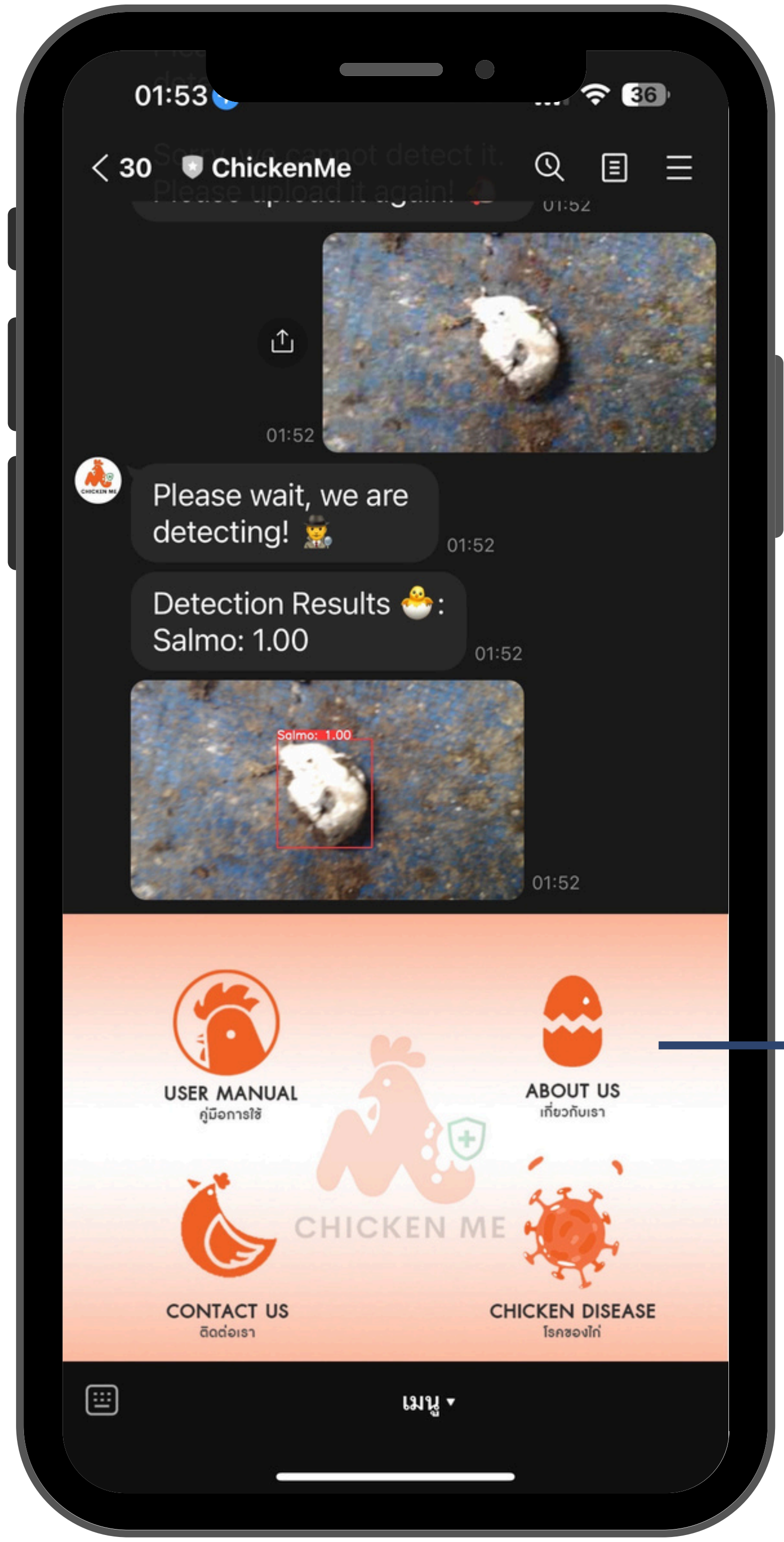
ChickenME GITBOOK



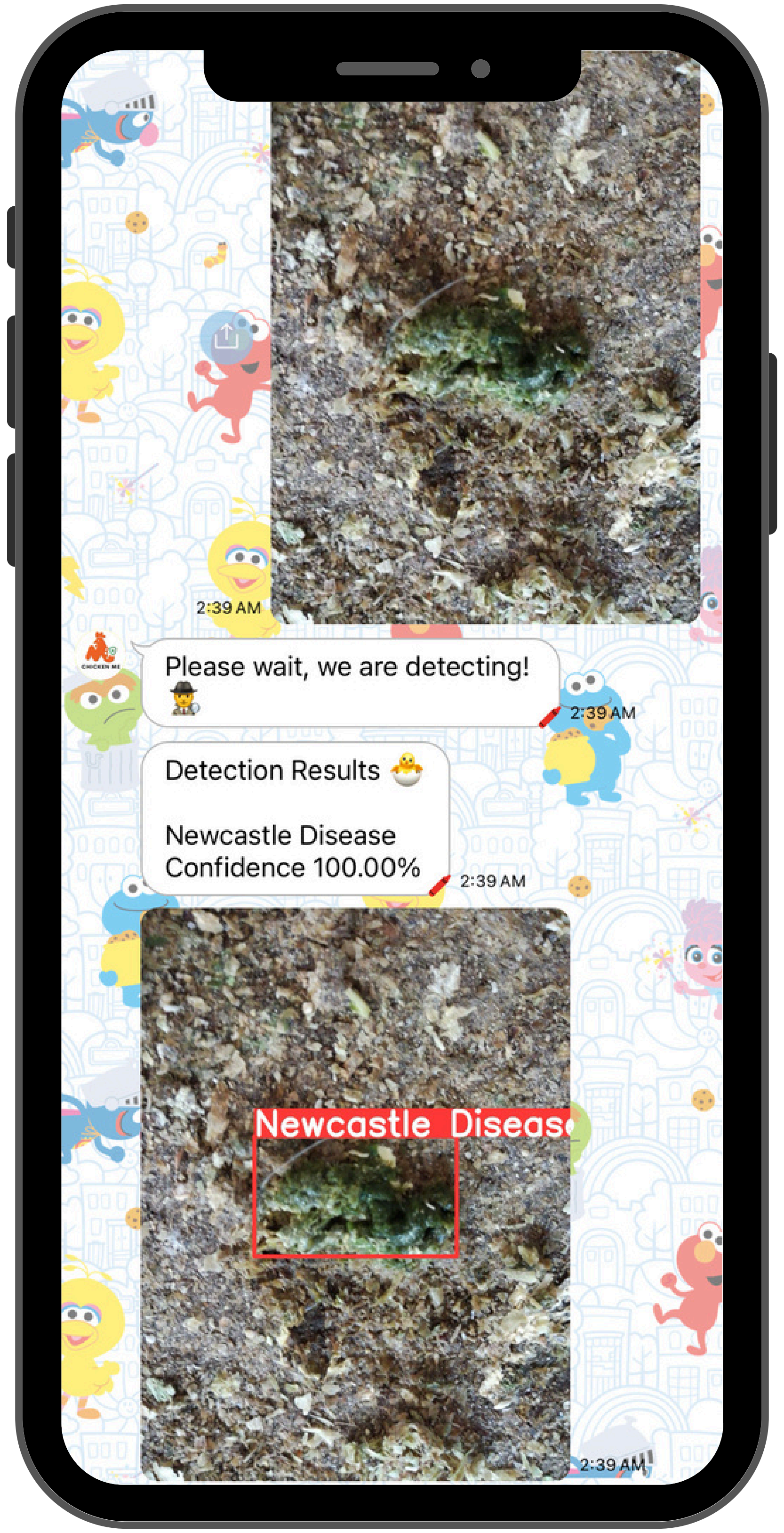
GitBook helps organize documents and keeps track of changes easily, making work smoother and teamwork better.

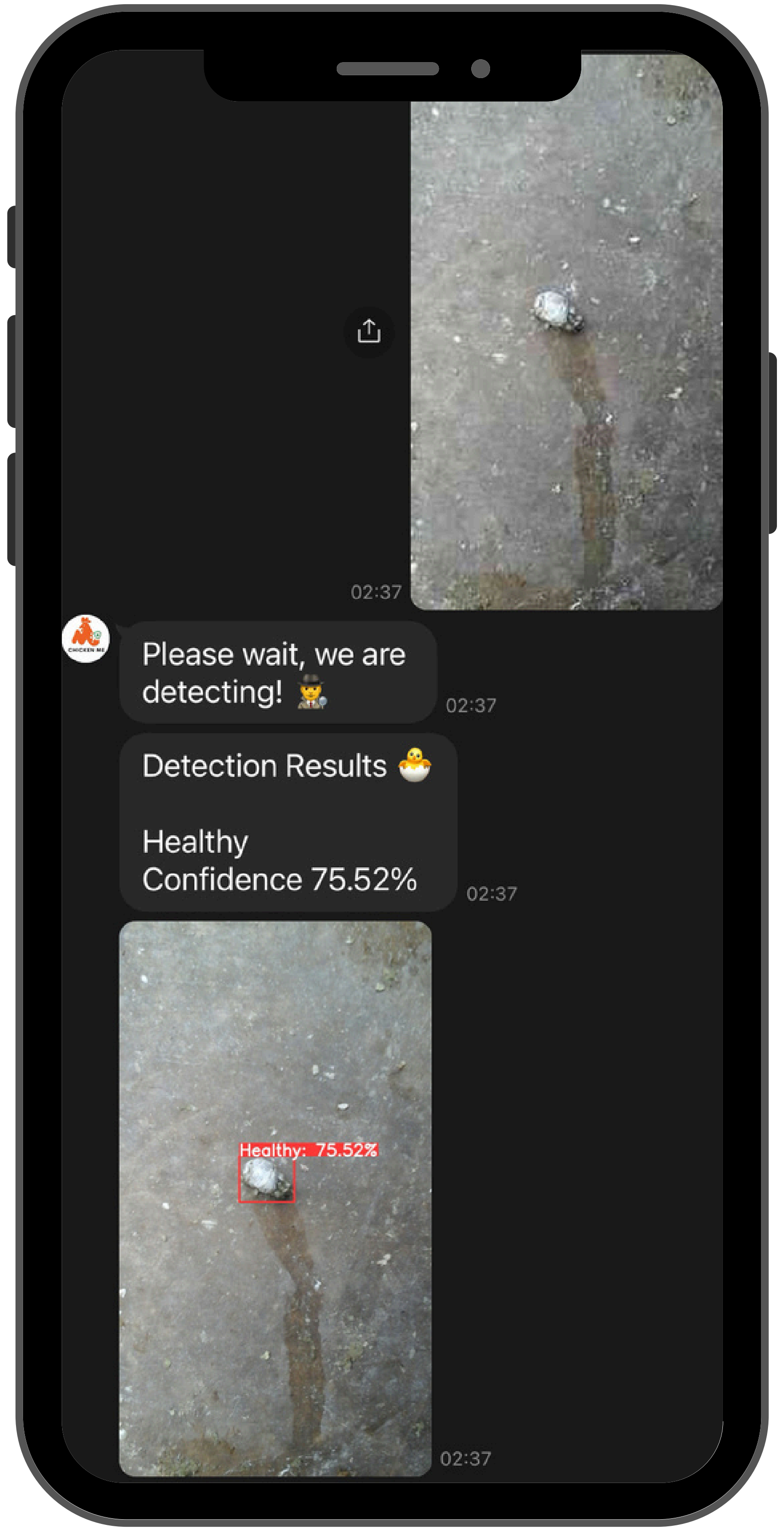
Embedded Link

GitBook

ChickenME LINE ACCOUNT

Example images of processed output that users will receive from ChickenME

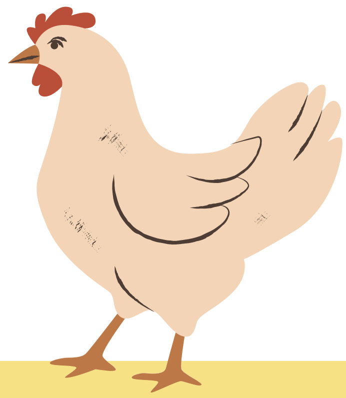




CONCLUSION AND DISCUSSION

CONCLUSION

- ChickenME utilized YOLOv5 for object detection and ResNet50 for image classification to classify the diseases in chickens.
- Classification of health conditions into healthy and three common diseases: Coccidiosis, Salmonella, and Newcastle Disease.
- Trained on a dataset of 10,500 chicken fecal images from Zenodo, ChickenME automates disease detection. With a split ratio of 90/10.
- From the experiments, YOLOv5 gave a better result than YOLOv3 when training on the same hyperparameter and settings.
- Integrated within the LINE platform, it offers user-friendly access and aims to decrease manual observation for time-efficient deployment.



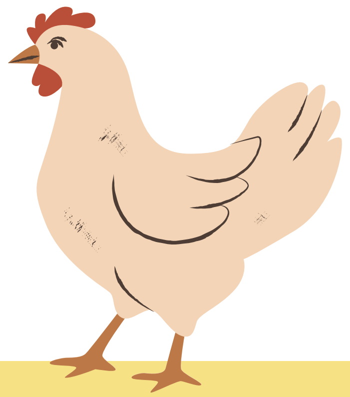
LIMITATIONS

- ChickenME's current limitation is its limited disease classification range. It identifies common diseases but may miss other significant poultry diseases.
  - lead to undetected conditions affecting poultry health and farm productivity.

- Hardware and resource limitations affect model development
  - Restricted computational power
  - Limited memory and slower processing times

FUTURE WORK

- The enhancement of ChickenME aims to expand disease classification beyond current inclusions.



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ChickenME

DEMONSTRATION

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ChickenME

DEMONSTRATION

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THANK YOU

Q&A session