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Case Study Zimbabwe

A DEEP LEARNING BASED APPROACH FOR FOOT AND MOUTH DISEASE DETECTION

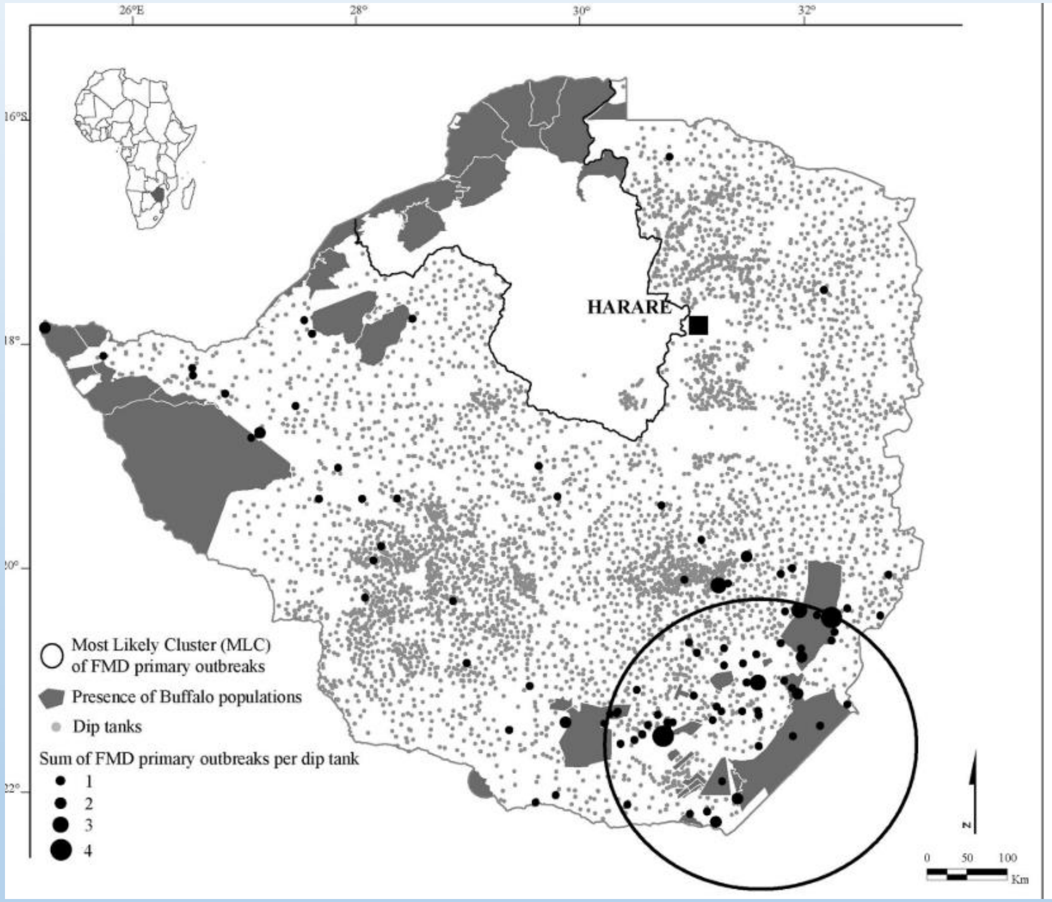
Foot and Mouth Disease

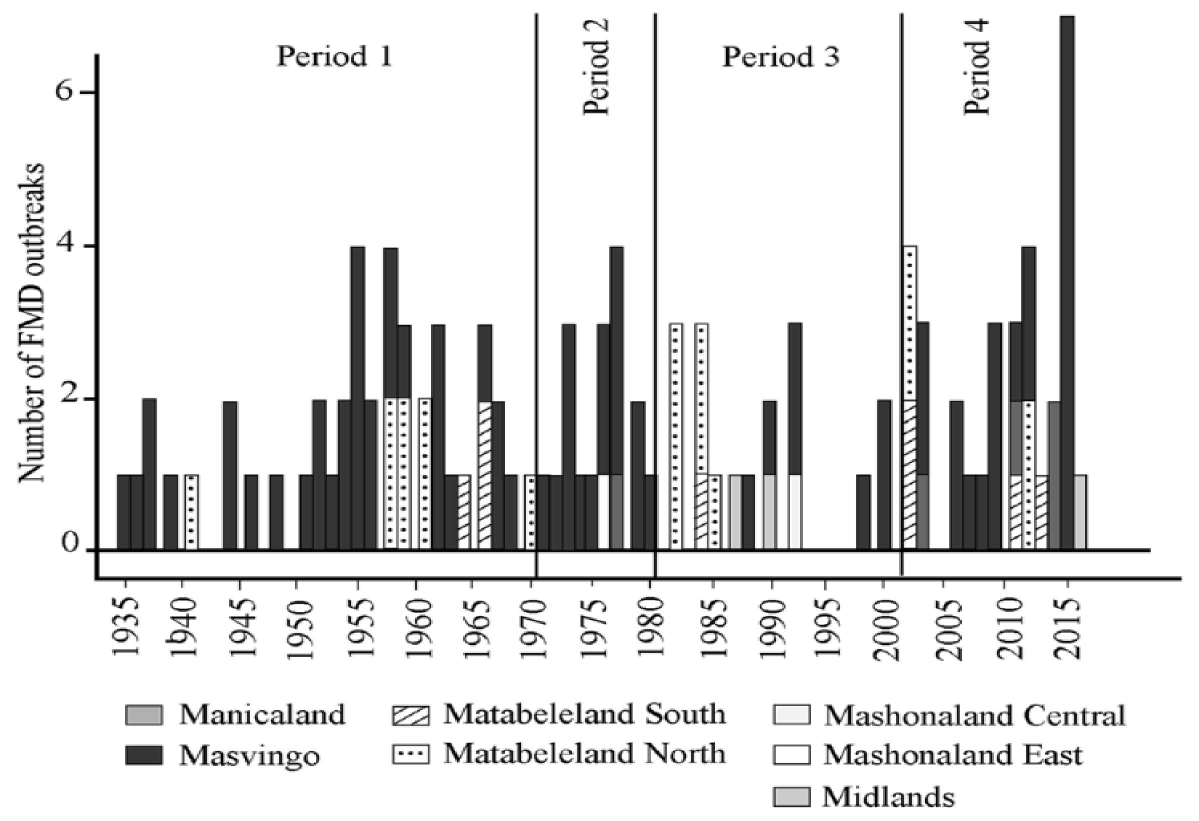
Infectious livestock disease caused by the Foot and Mouth Disease Virus (FMDV)

Affects cloven-hoofed domestic animals and around 70 wild creature species

African Buffalo, including cows, pigs, and little ruminants

Foot and Mouth Outbreaks in Zimbabwe from 1931 to 2016



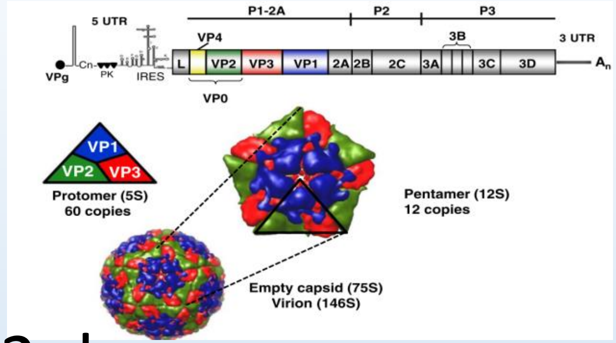


(Guerrini *et al.*, 2019)

Foot and Mouth Serotypes

- 7 distinct serotypes (O, A, C, Asia 1, SAT 1, 2, & 3) and there are some subtypes in each serotype.
- **Serotypes O** Oise France
- **Serotypes** A Allemagne in Germany.
- **Serotypes** SAT Southern African Territory

Foot and Mouth

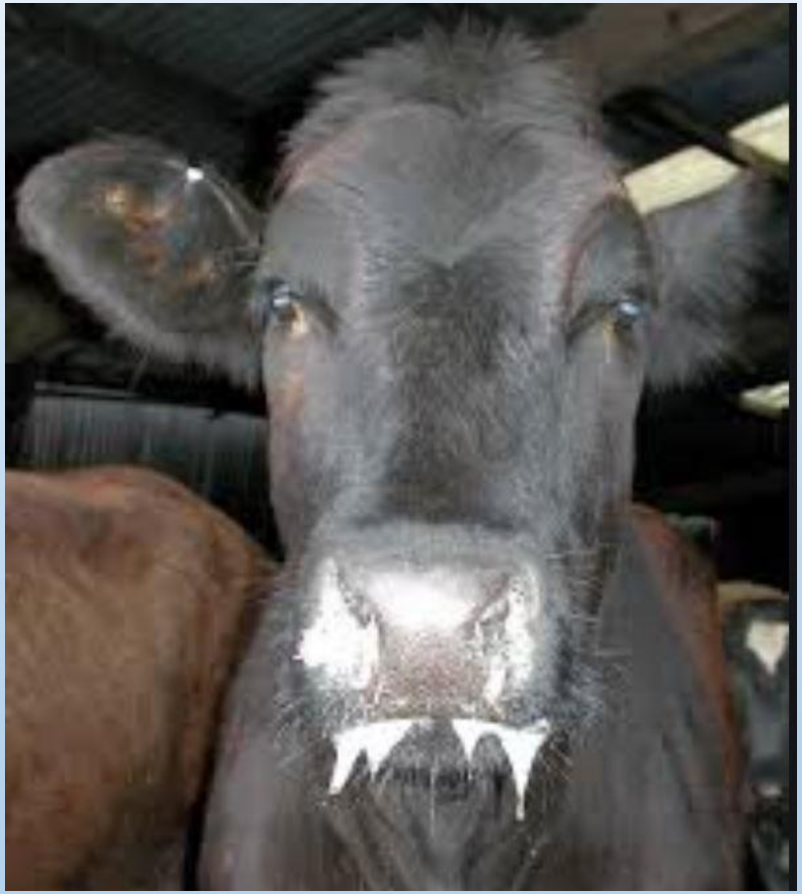


- The incubation period of FMD is between 2-12 days
- Animals can experience high fever with temperatures 104 -106 ◦F.
- Animals also develop blisters in the mouth (tongue, gum, lips) which later rupture and leave ulcers.
- Blisters also develop on the teats and feat of animals (Aftosa, 2015).
- However, confirmation of diagnosis can only be done after laboratory tests.

FMD Control Measures

- Early detection and reporting of the FMD to limit the spread of the disease
- II. Quarantining of the infected animals at the premised where it was detected
- III. Containing the spread of the disease by restricting the movement of the animals from the premises.
- IV. Vaccination of cattle to eradicate the disease
- V. Continuous surveillance in the FMD prone diseases

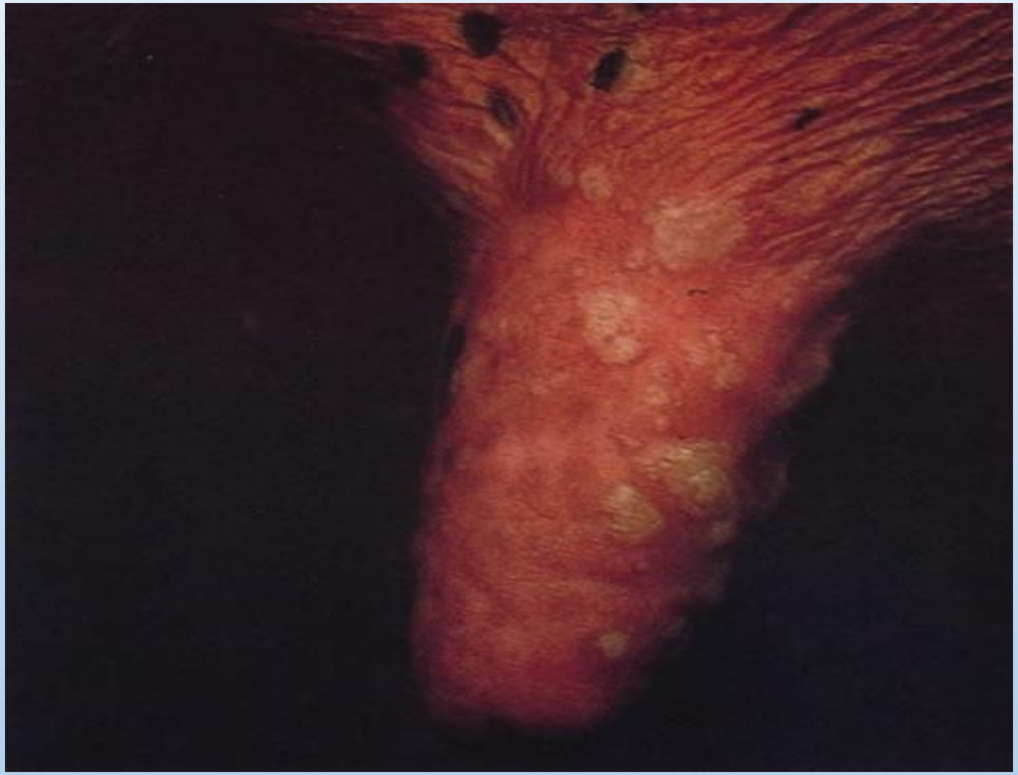
Foot and Mouth Symptoms -Cattle



Drooling

Feet

Foot and Mouth Symptoms -Cattle



Gum lesion

Teat lesion

Deep learning

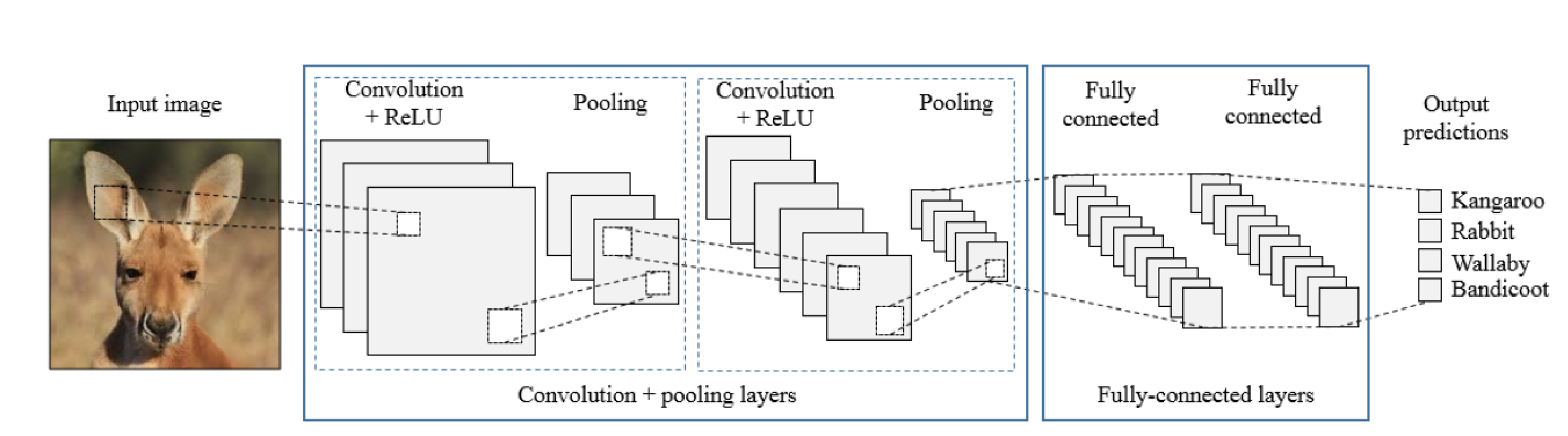


Illustration of a typical convolutional neural network architecture setup (Nguyen et al, 2017).

Deep learning

- Deep learning is a specific subfield of machine learning:
- a new take on learning representations from data that puts an emphasis on learning successive layers of increasingly meaningful representations.
- Deep means stands for this idea of successive layers of representations.
- How many layers contribute to a model of the data is called the depth of the model

Problem Statement

There is a shortage of veterinary specialists across the country due to brain drain which leaves farmers cattle vulnerable, timeous advice for the detection of FMD as the diseases leads to loss of production of livestock meats and also milk to farmers and also a major impediment as countries with foot and mouth faces trade restrictions moreover the disease is difficult and costly to control and eradicate.

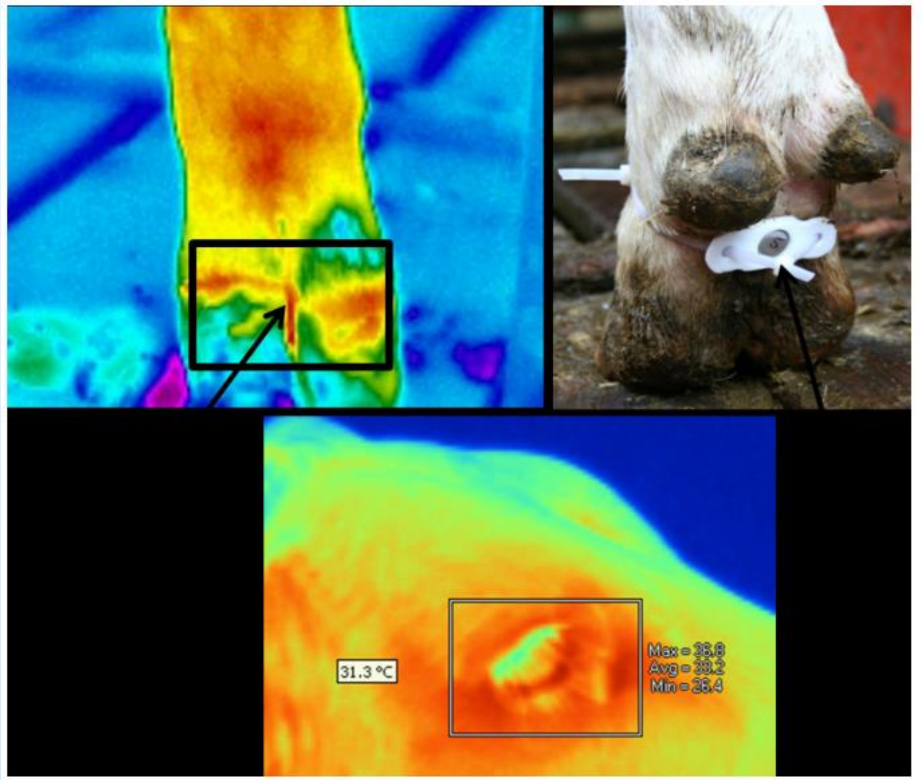
Aim

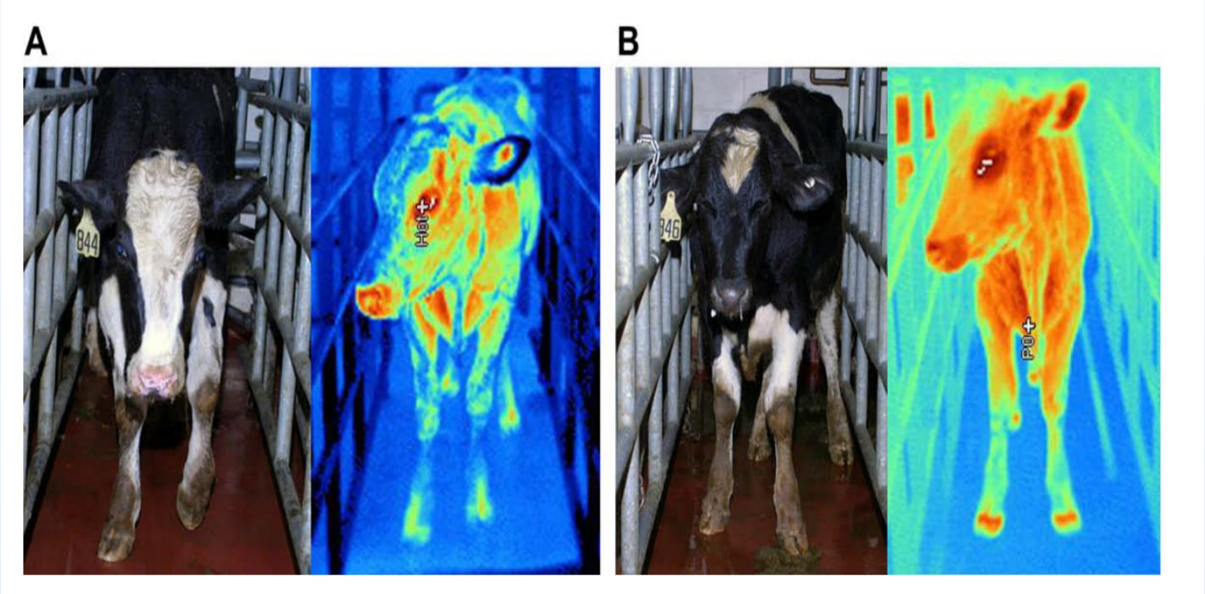
- To investigate how deep learning architectures can be used to detect foot and mouth

Objectives

i. Detection of foot and mouth disease using deep learning architectures;
ii. Assessment of deep learning architecture model performance for the detection of foot and mouth disease;
iii. Recommendation of a system for capturing images used in detection of foot and mouth disease.

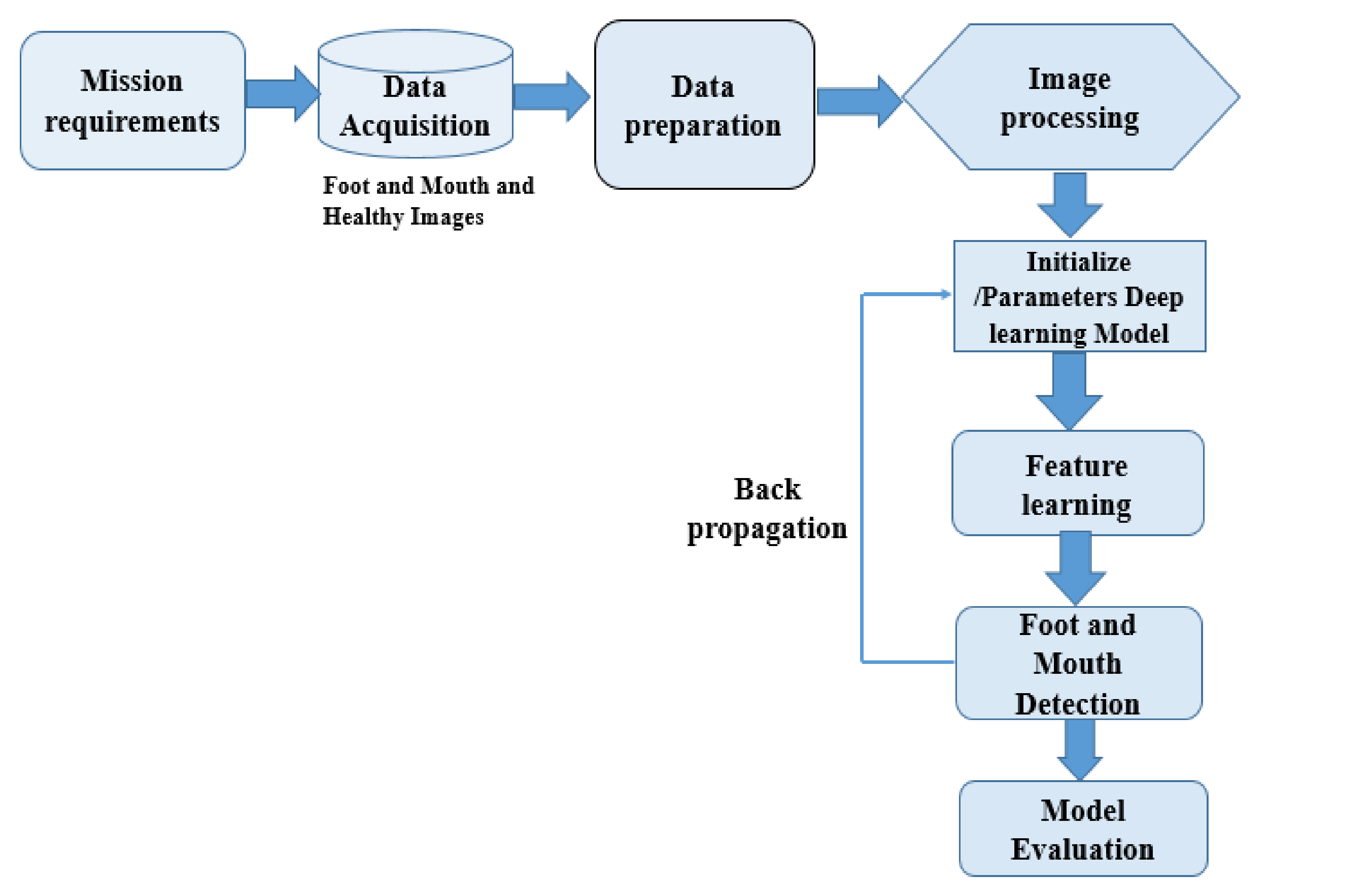
Related work





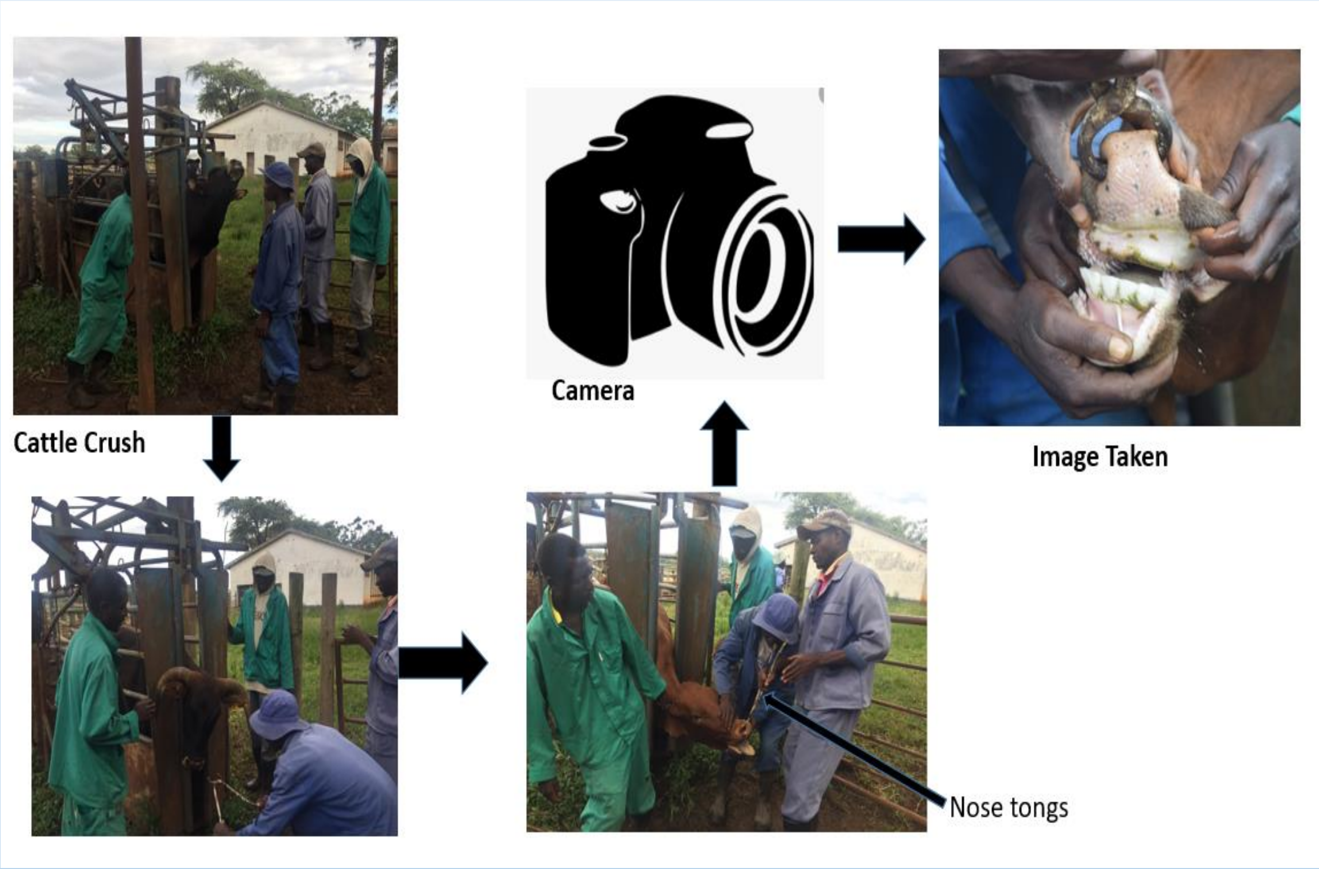
Digital and infrared images of cattle without (A) or with (B) fever and note that the lower temperatures (blue-green) in the animal without fever or viremia versus the higher temperatures (orange-red) in the viremic and feverish animal.

Material and Methods



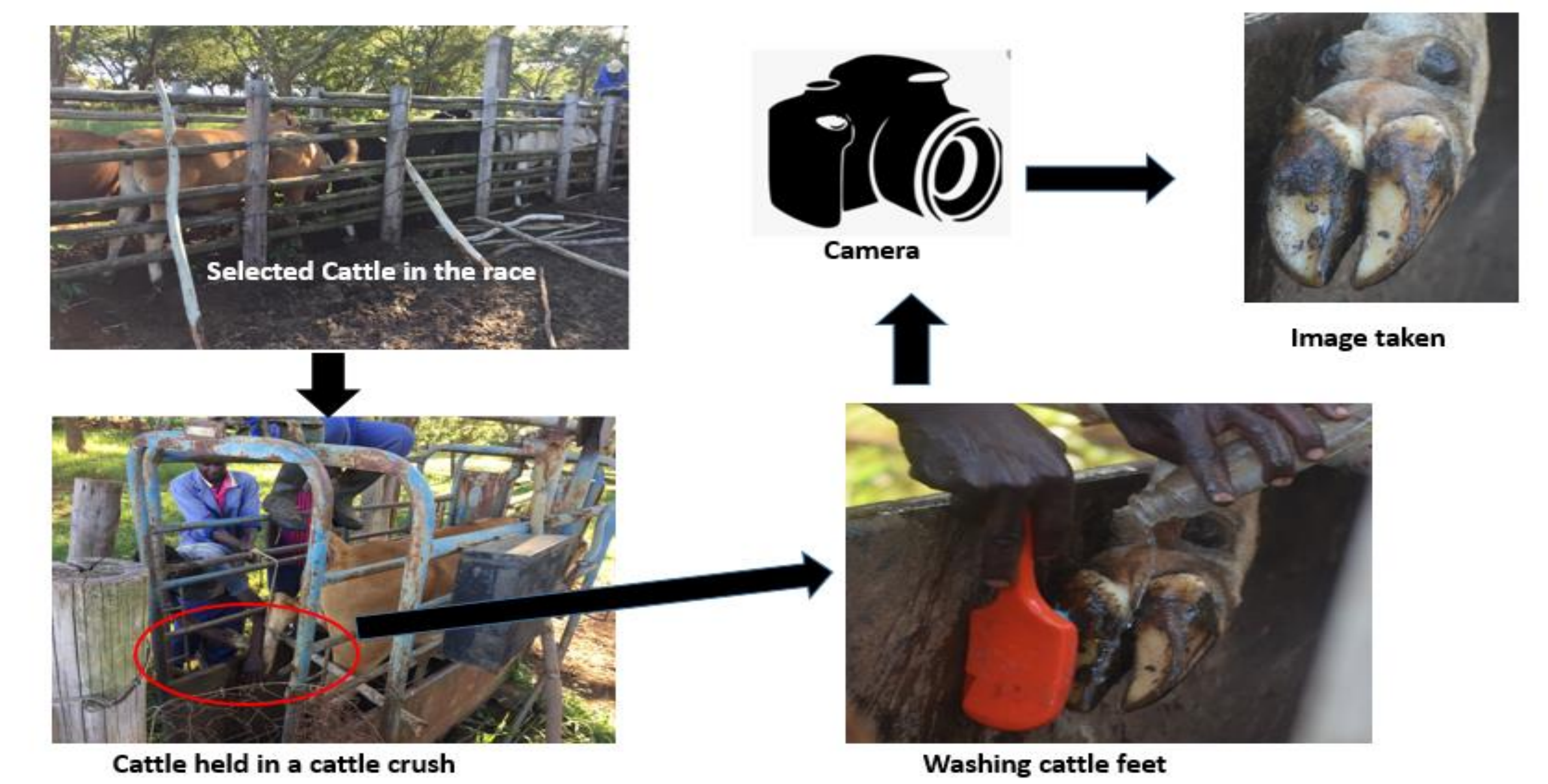
Acquisition of Healthy cattle images

Images taken whilst cattle were grazing



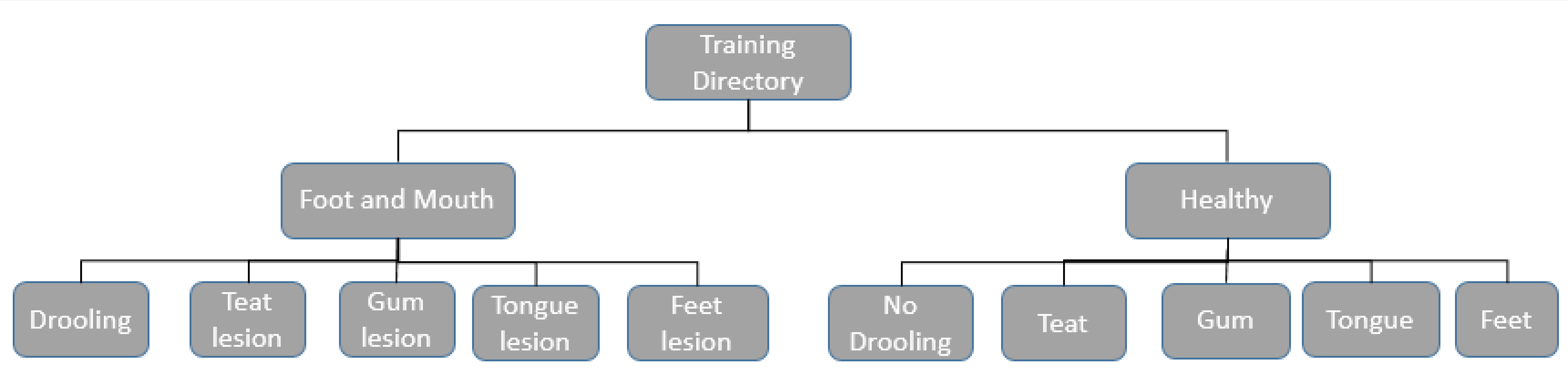
Process for taking images for tongue, gum and teats

Acquisition of Healthy cattle images

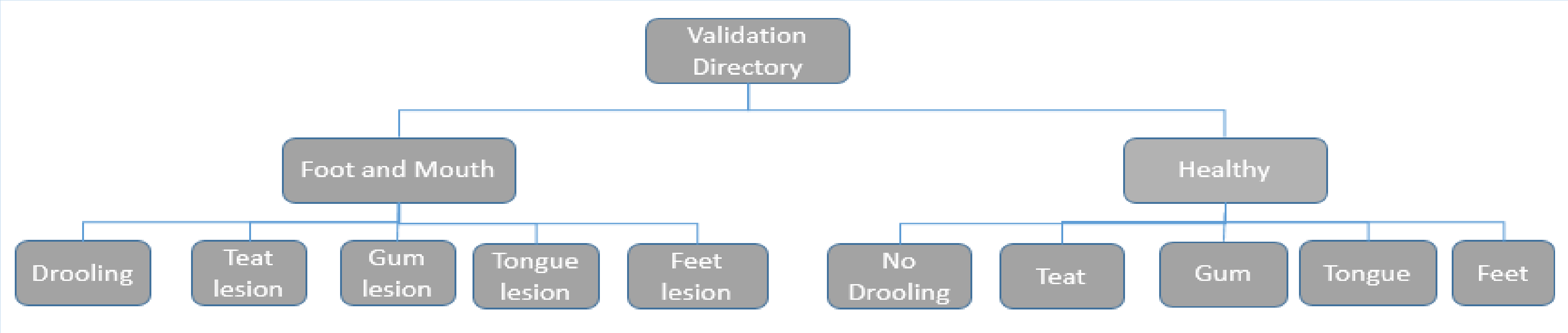


Process for taking images of the feet

Data Préparation



Training Directory



Validation Directory

Preprocessing -Selection of area of interest

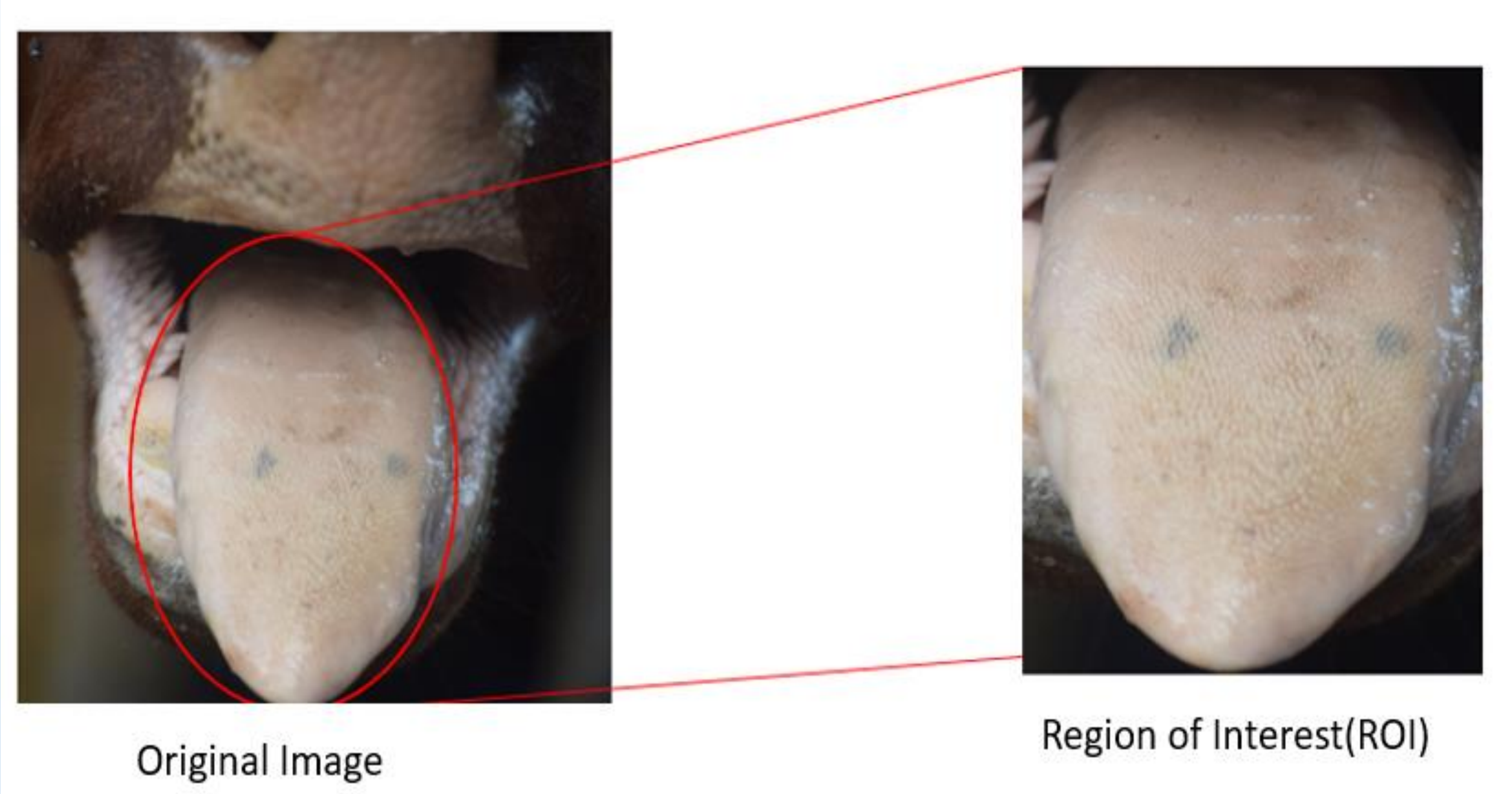
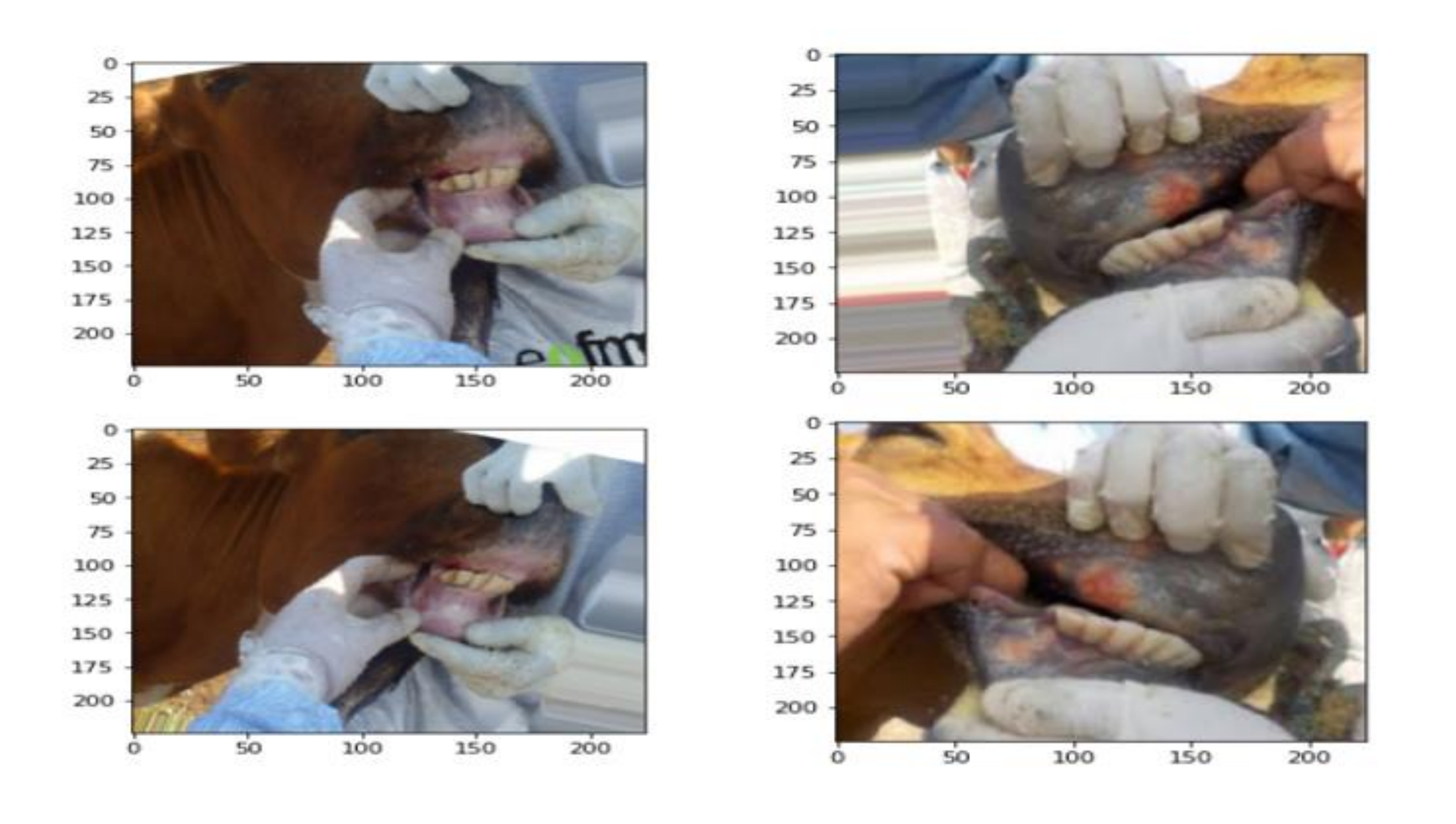
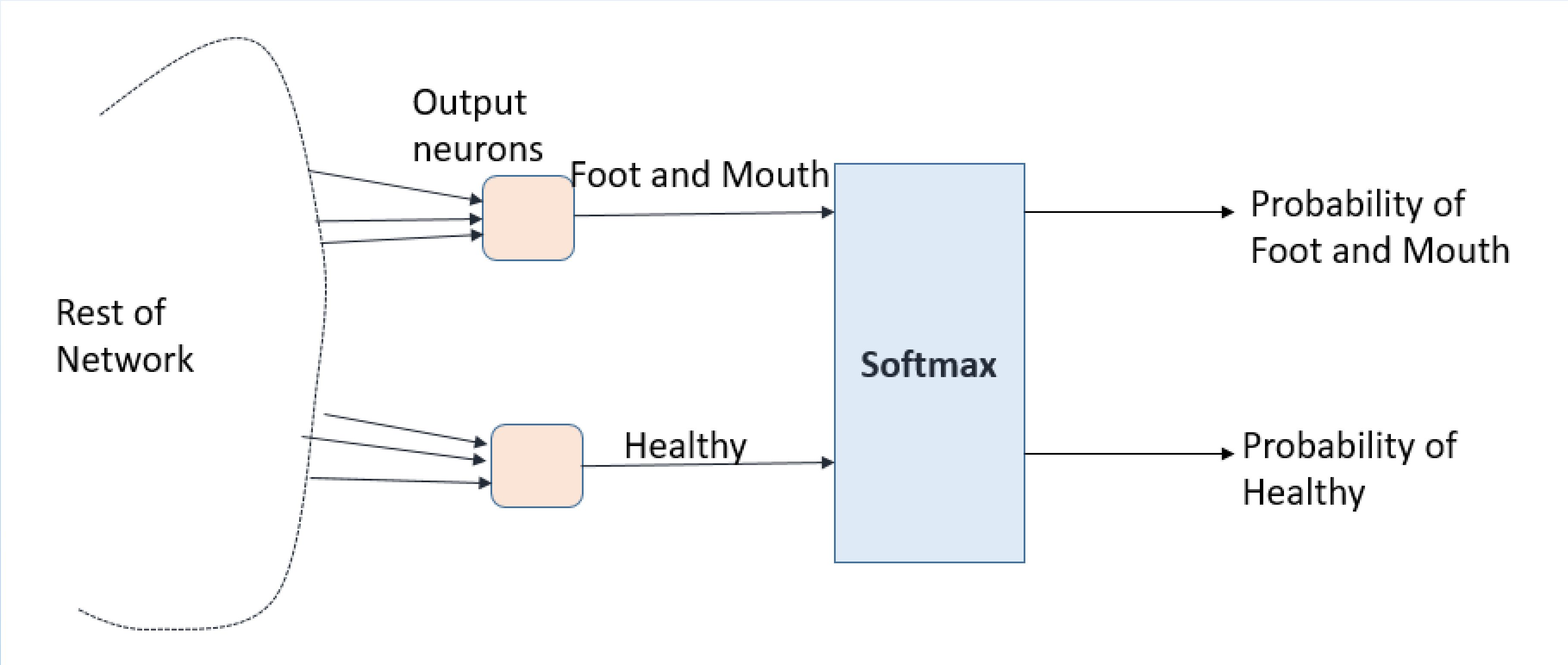


Image Augmentation

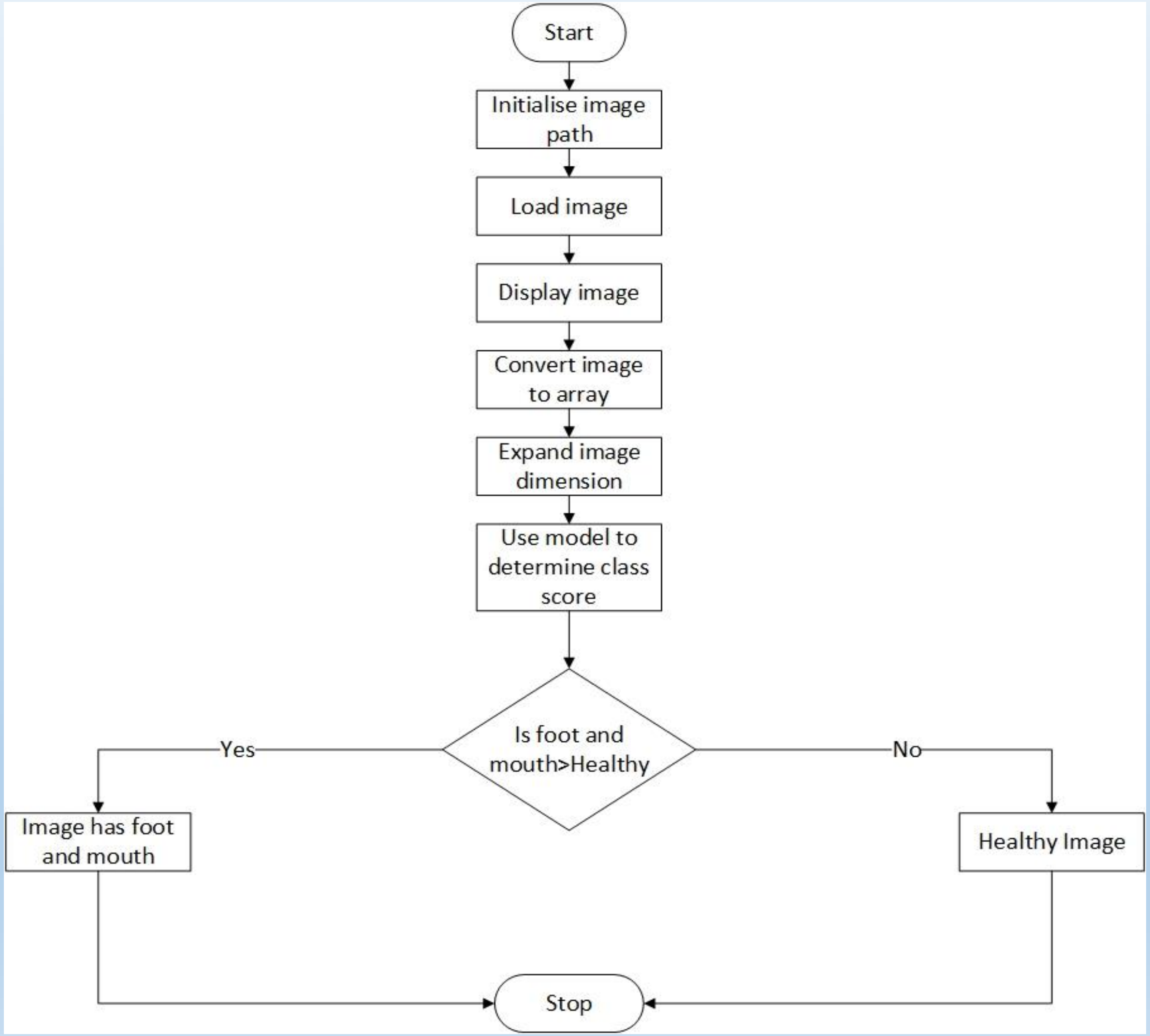


Foot and Mouth Detection



Softmax classifier outputs the probability of an image belonging to a certain type of class e.g. foot and mouth disease or healthy class.

Procedure for detecting



Risk Management

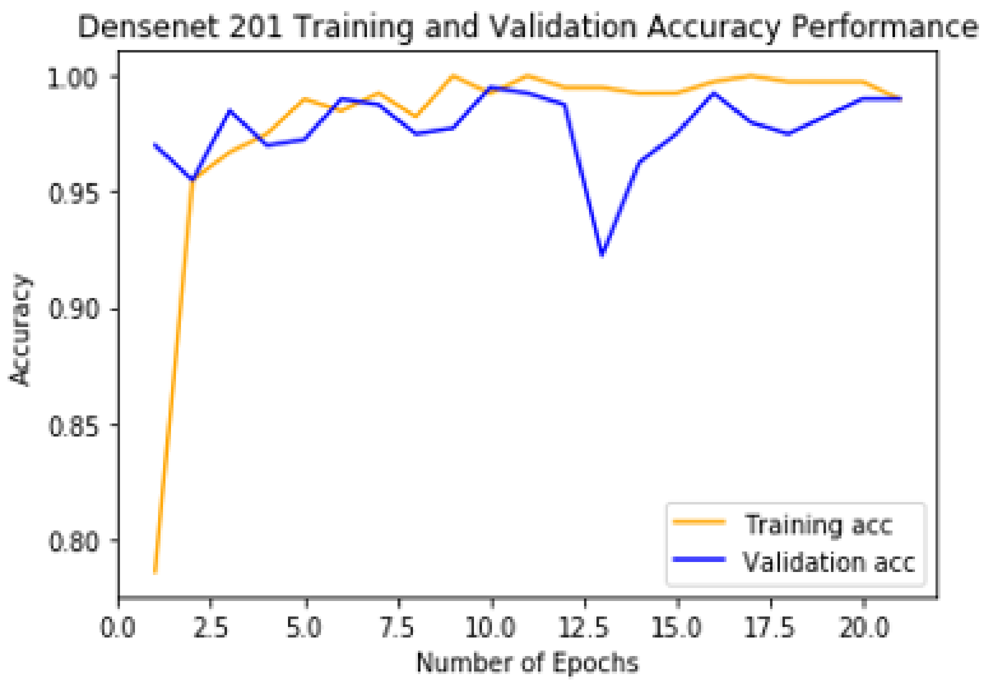
Risk	Counter Measure
Failure to get images from the Veterinary department	Request from International Organisations dealing with Foot and Mouth (EuFMD, Pirbright Institute) Download from the Internet
Few images	Data Augmentation Image Pre-processing of healthy cattle and pre-process them introducing diseases Transfer learning
Cattle feet in a muddy farm	Isolate the cattle and wash their feet before taking pictures
Large training time required for CPU	Use Google Colab Graphical Processing Unit (GPU)
Google Colab resources are not guaranteed	Use the high-performance computer at the University of Zimbabwe

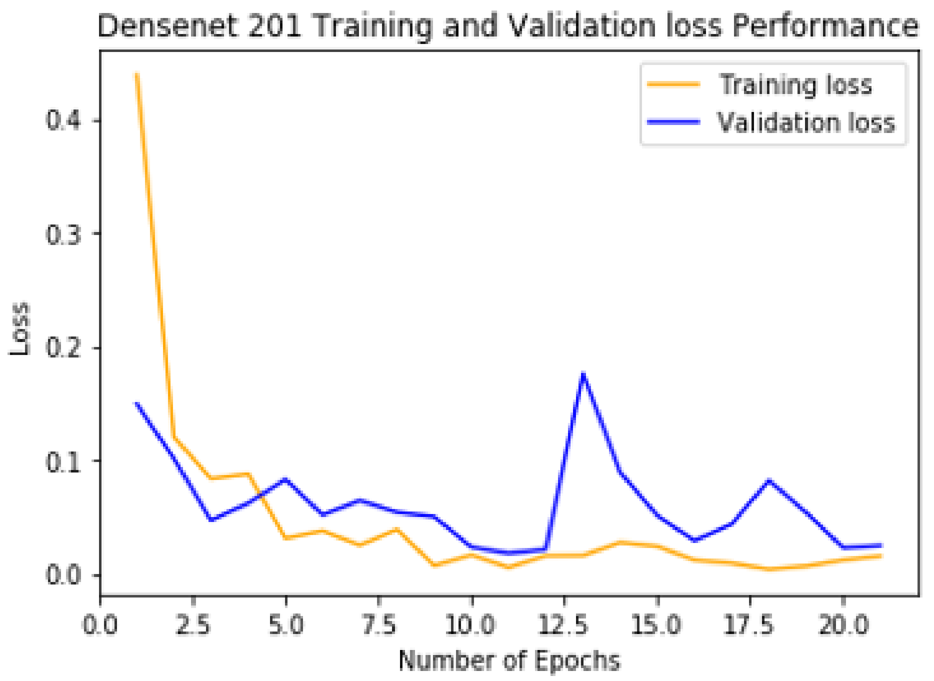
Results

Model	Layers	Params	Training Accuracy%	Validation Accuracy%	Training loss	Test Accuracy	Test loss
Inception V3	48	41.2M	0.9950	0.9525	0.0208	98.44	6.91
VGGnet	16	119.6M	0.8995	0.9300	0.314	79.69	50.11
Resnet	50	23.6M	0.9950	0.9850	0.0163	95.31	8.43
Resnet	152	58.5M	0.9825	0.9575	0.0367	100	8.70
Densenet 201	121	7.1M	0.9900	0.9900	0.0152	96.87	7.05

M Million

Densenet 201





Evaluation Metrics

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

Where;

- TP, FP, and FN represent the true positives, false positives and false negatives.

Confusion Matrix

- **True Positive TP**: cases when classifier predicted **TRUE** (they have the disease-Foot and Mouth) and the correct class was **TRUE** (cattle has the disease- Foot and Mouth)

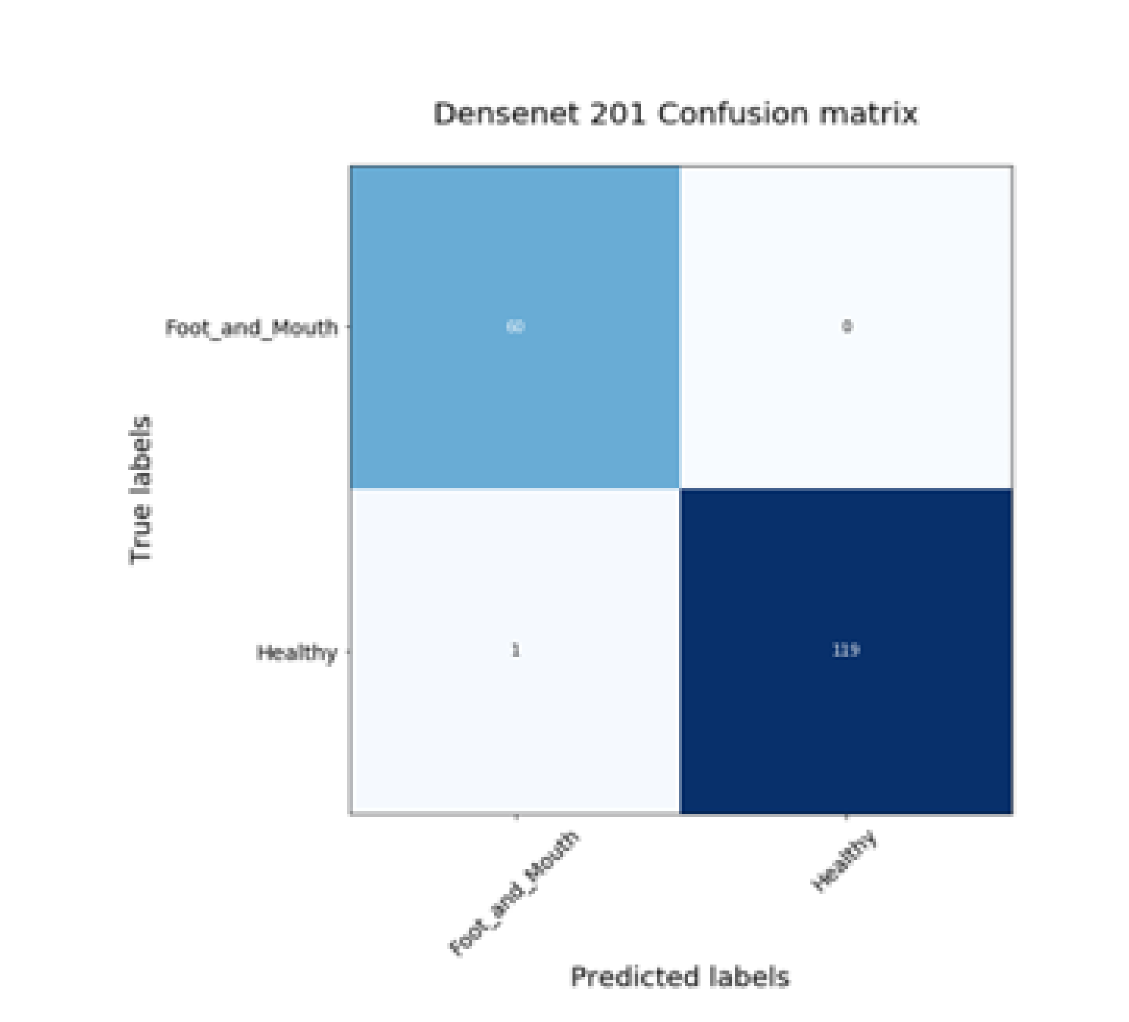
- **True Negative TN**: cases when the model predicted **FALSE** (no disease-Healthy) and the correct class was **FALSE** (cattle do not have the disease-Foot and Mouth)

- **False Positive FP**: (Type I error): classifier predicted **TRUE** but correct class was **FALSE** (cattle did not have the disease)

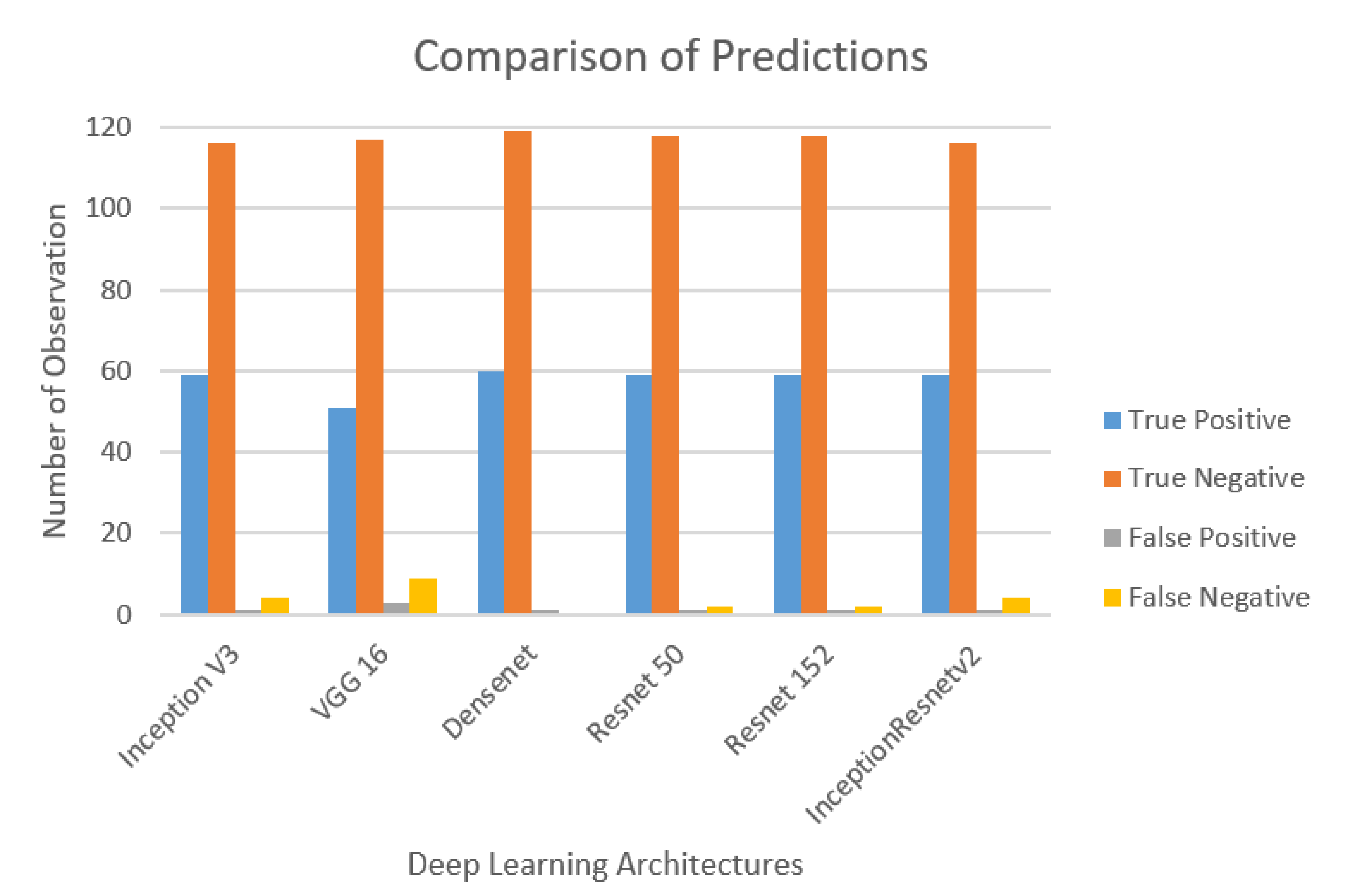
- **False Negatives FN:** (Type II error): classifier predicted **FALSE** (cattle do not have the disease-Foot and Mouth) but they do have the disease

Confusion Matrix

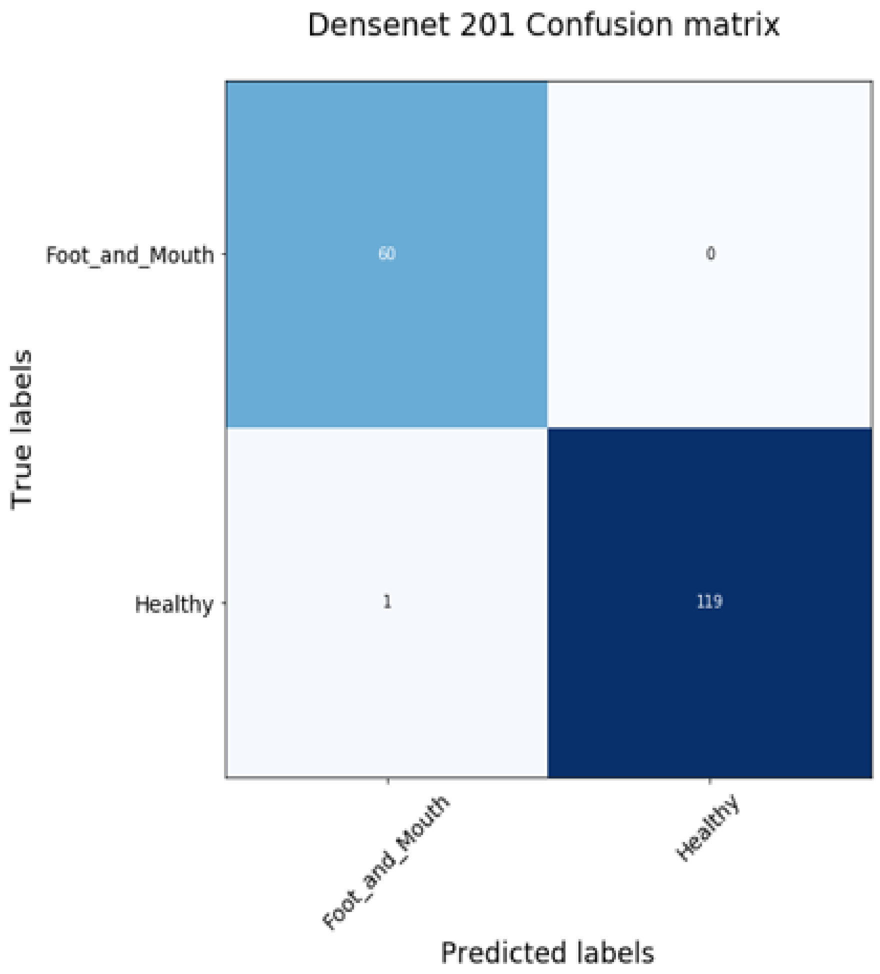
	(Predicted)	(Predicted)
(Actual)	True Positive (TP)	False Positive (FP)
Actual)	False Negative (FN)	True Negative (TN)



Comparison of the Predictions



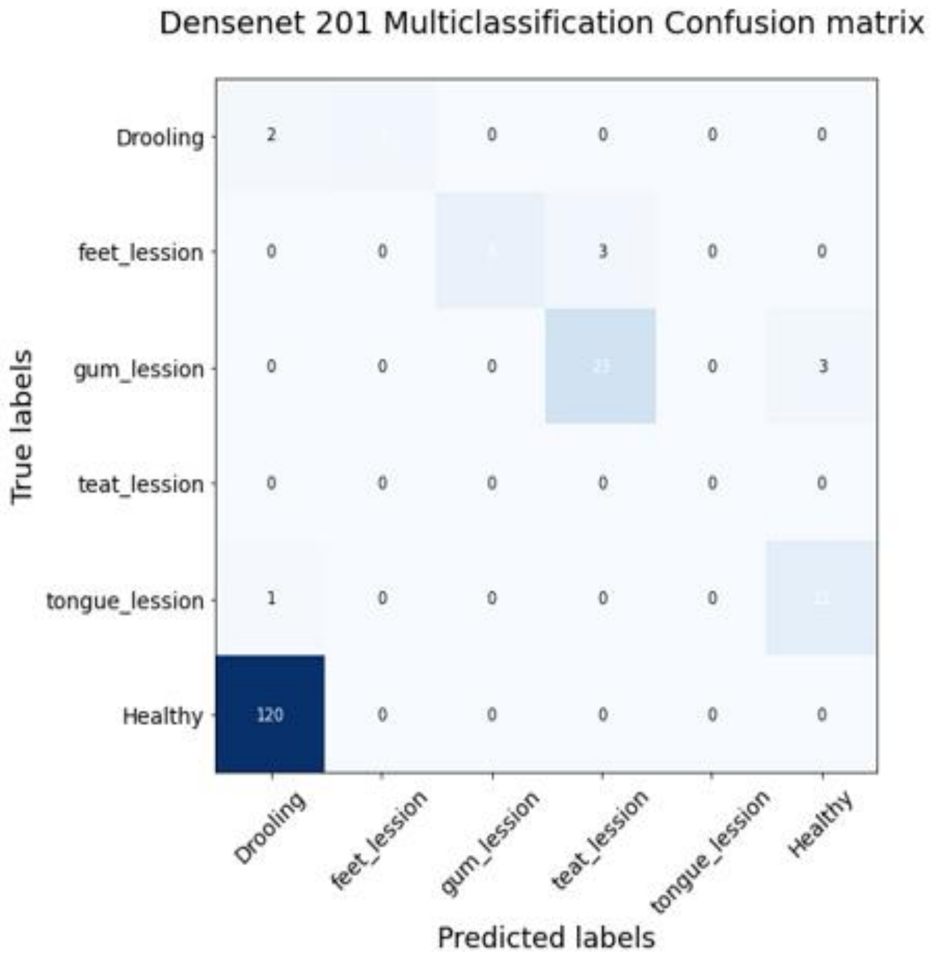
Densenet Confusion Matrix



Densenet 201 Classification Report

	precision	recall	f1-score	support
Foot_and_Mouth	0.98	1.00	0.99	60
Healthy	1.00	0.99	1.00	120
accuracy			0.99	180
macro avg	0.99	1.00	0.99	180
weighted avg	0.99	0.99	0.99	180

Densenet Multiclassification



Densenet 201 Multiclass Classification Report

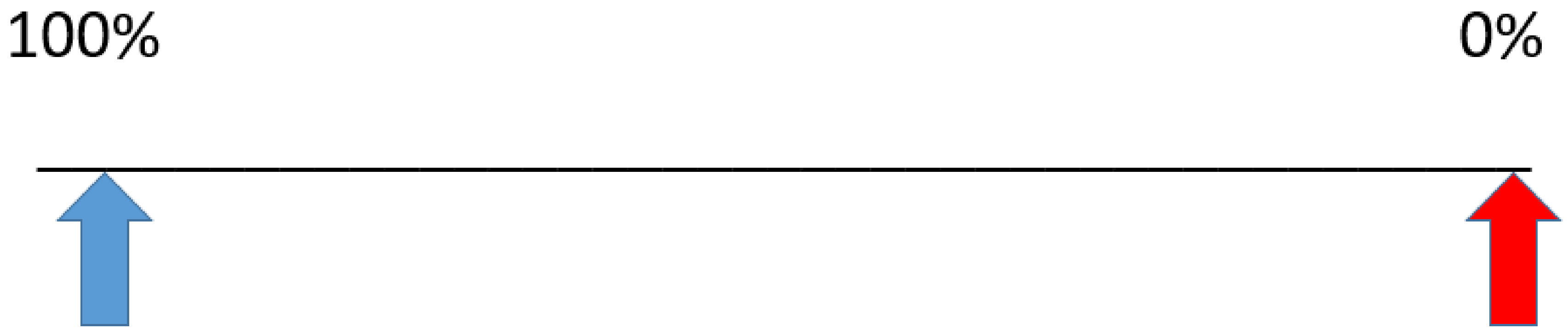
	precision	recall	f1-score	support
Drooling	0.02	0.40	0.03	5
feet_lession	0.00	0.00	0.00	11
gum_lession	0.00	0.00	0.00	26
teat_lession	0.00	0.00	0.00	0
tongue_lession	0.00	0.00	0.00	12
Healthy	0.00	0.00	0.00	120
accuracy			0.01	174
macro avg	0.00	0.07	0.01	174
weighted avg	0.00	0.01	0.00	174

Comparison of the evaluation metrics

- **Sensitivity** is the probability that the screening test is positive given that cattle have foot and mouth disease
- **Specificity** is the probability that the screening test is negative given that cattle do not have the foot and mouth disease
- **Sensitivity =**$\boldsymbol{truepositiverate}$: $\boldsymbol{TPR = \frac{positive\ correctly\ classified}{total\ positives} = \frac{TP}{TP+FN}}$

- $\boldsymbol{Specitivity = truenegativerate}$: $\boldsymbol{FNR = \frac{negative\ correctly\ classified}{total\ negatives} = \frac{TN}{FP+TN}}$

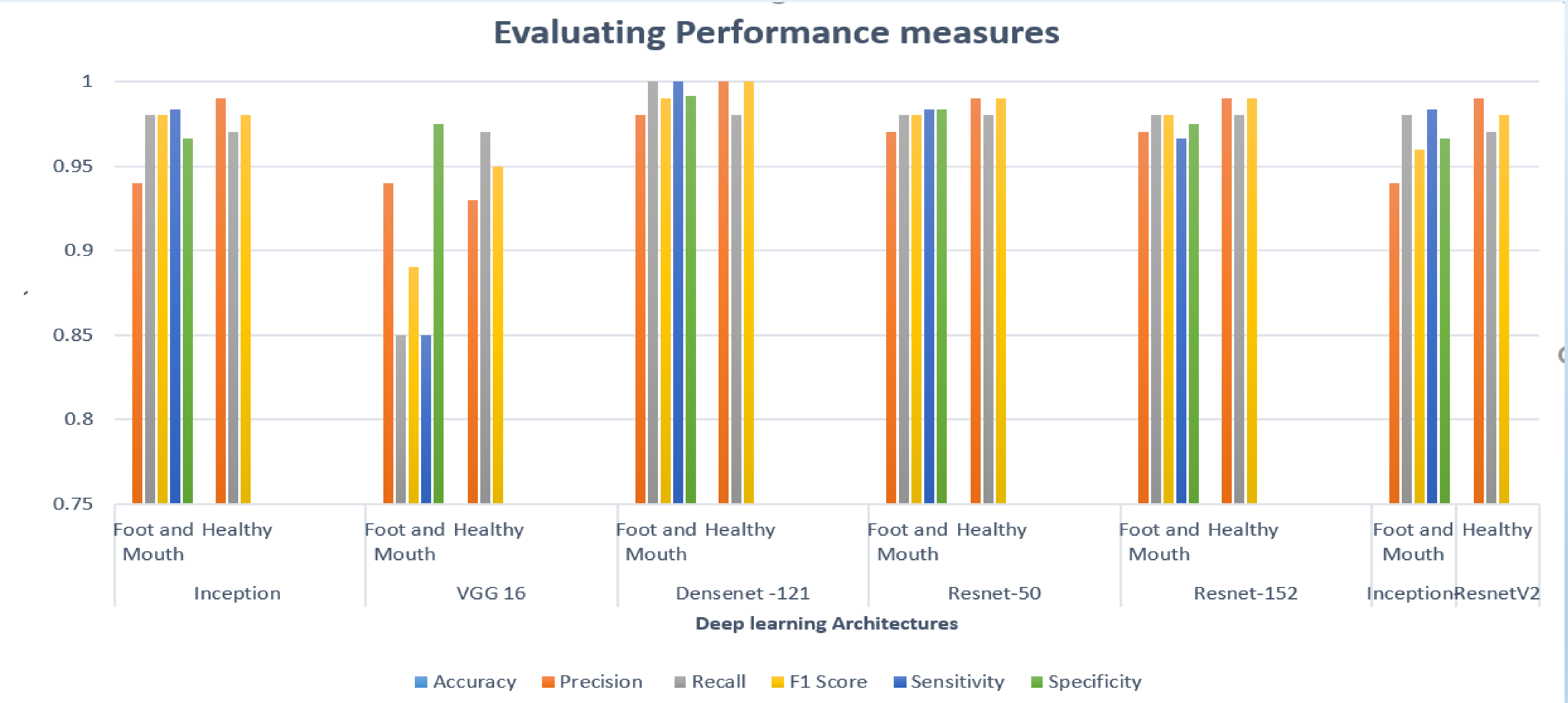
Specificity and Sensitivity



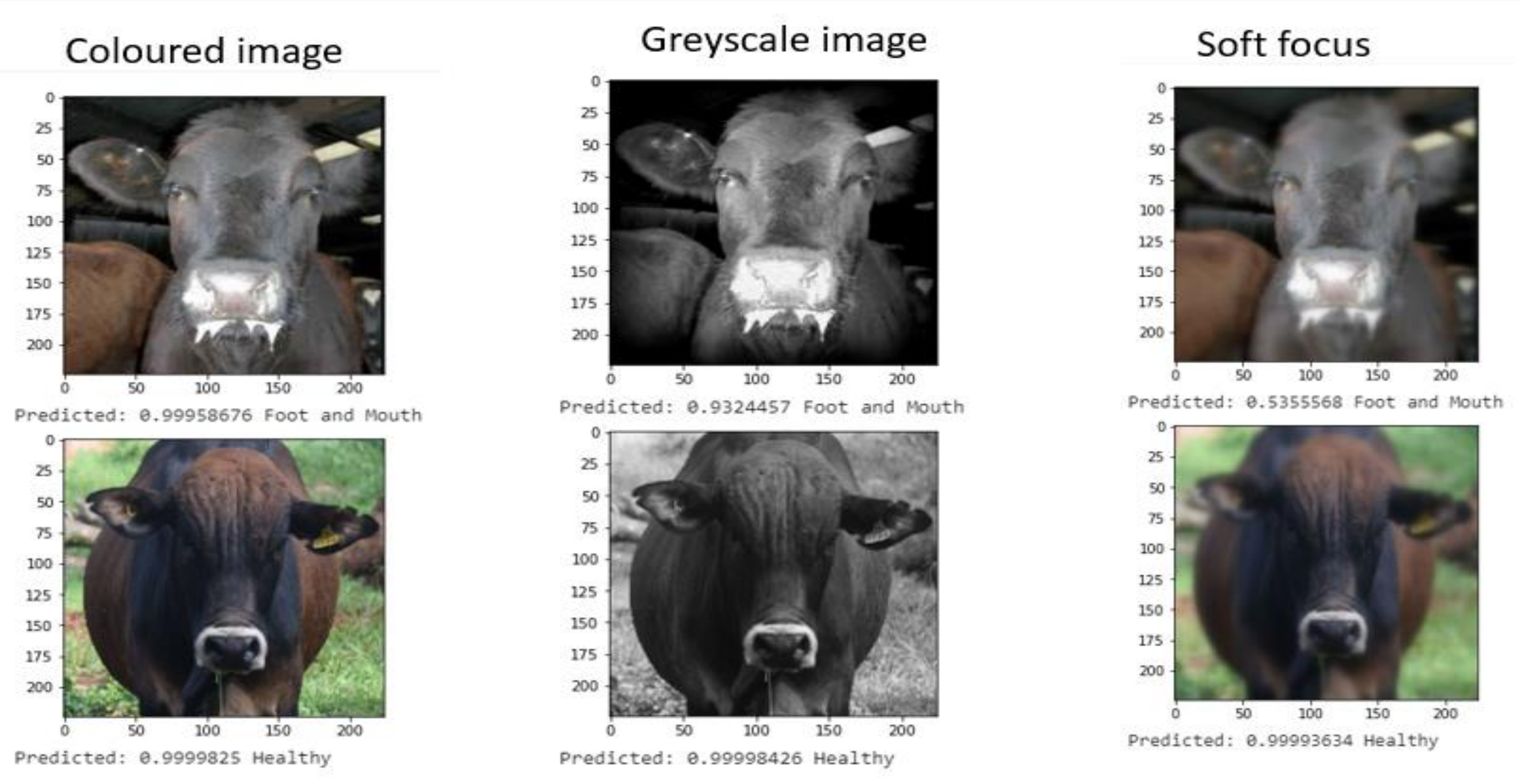
Specificity :All the health cattle labelled as healthy
Sensitivity :All Foot and Mouth diseased(unhealthy) cattle labelled as unhealthy

Specificity :All the health cattle labelled as diseased with Foot and Mouth (unhealthy)
Sensitivity :All Foot and Mouth diseased(unhealthy) cattle labelled as healthy

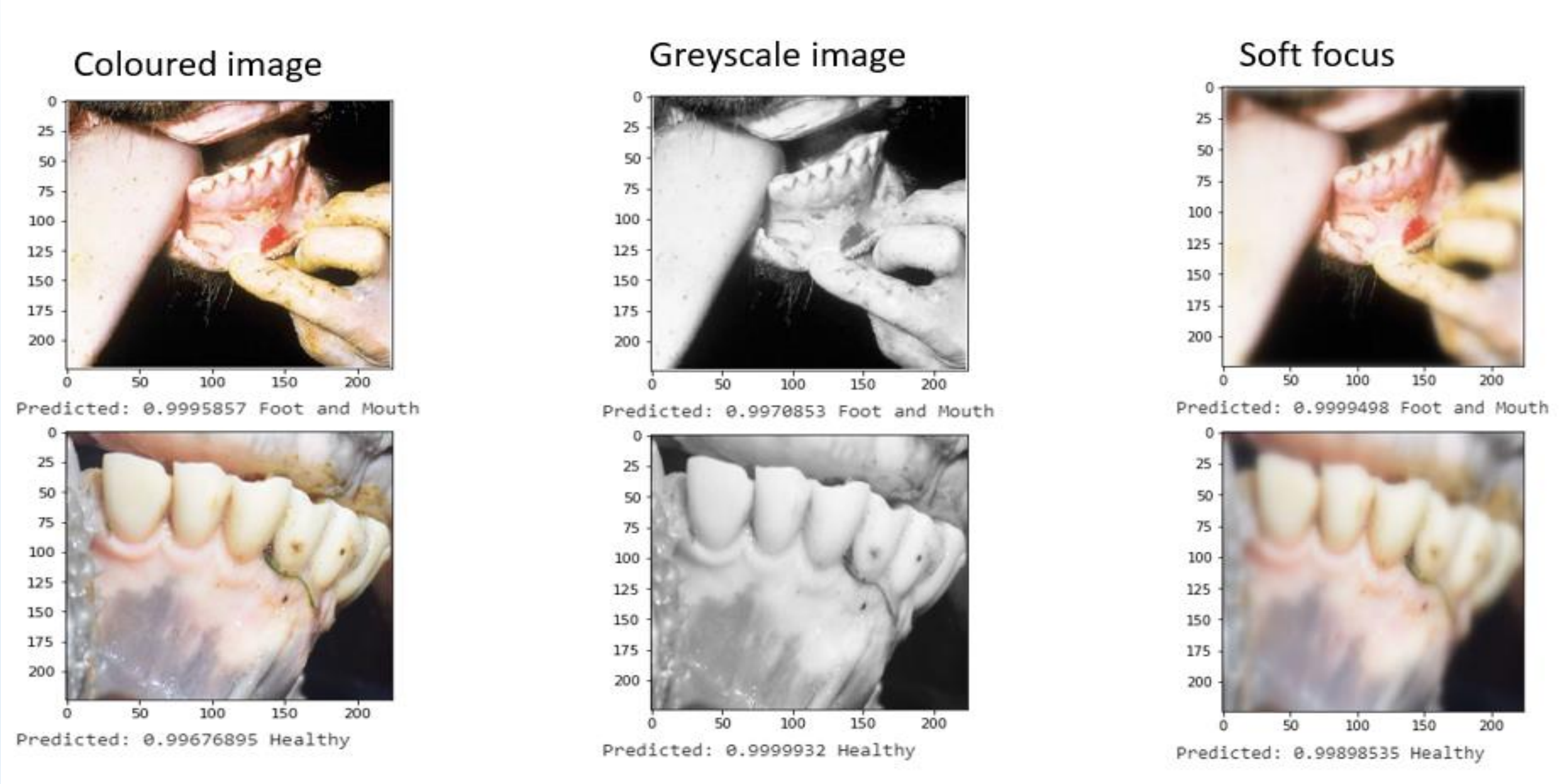
Evaluating Performances



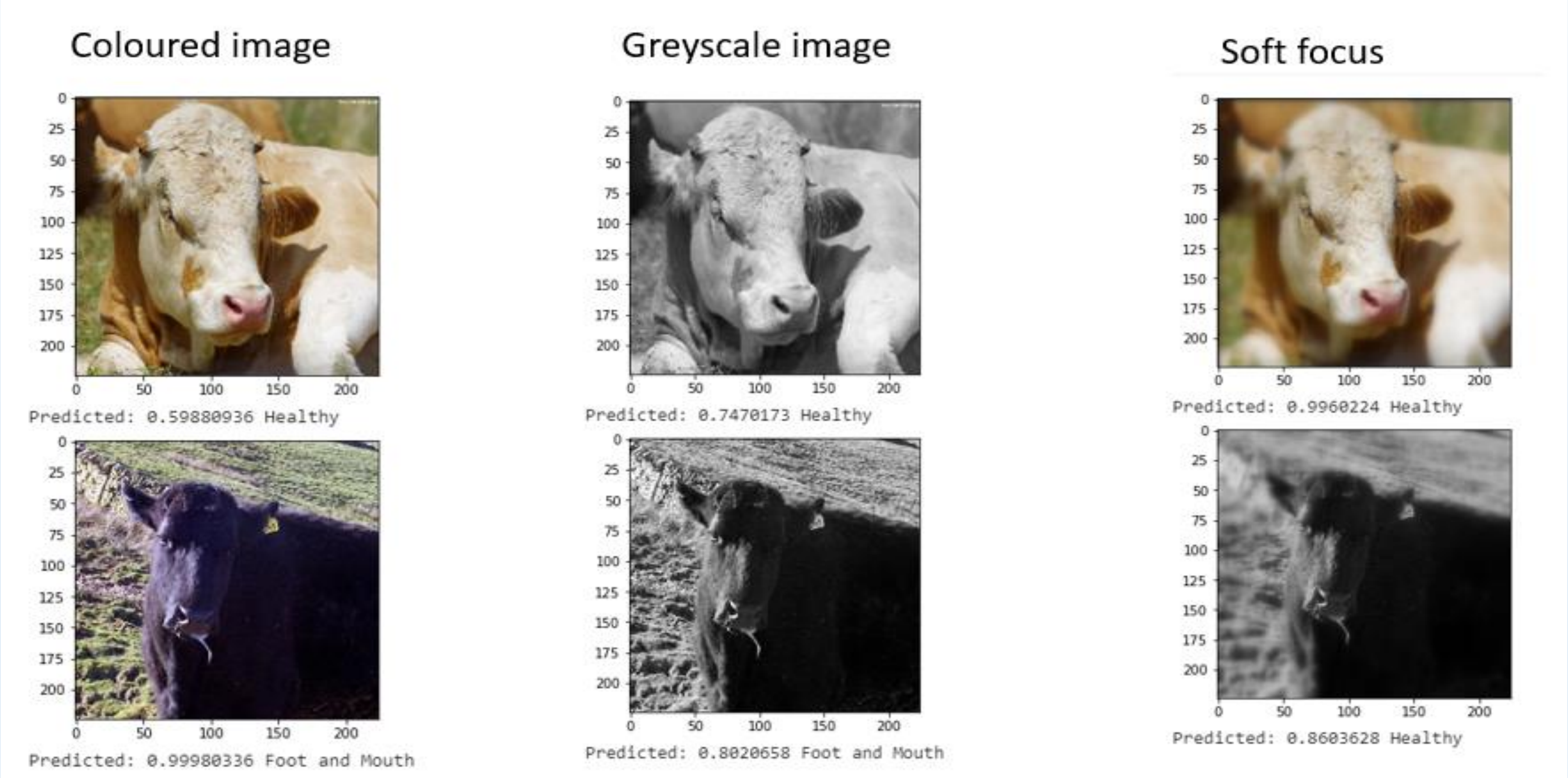
Predictions on test images



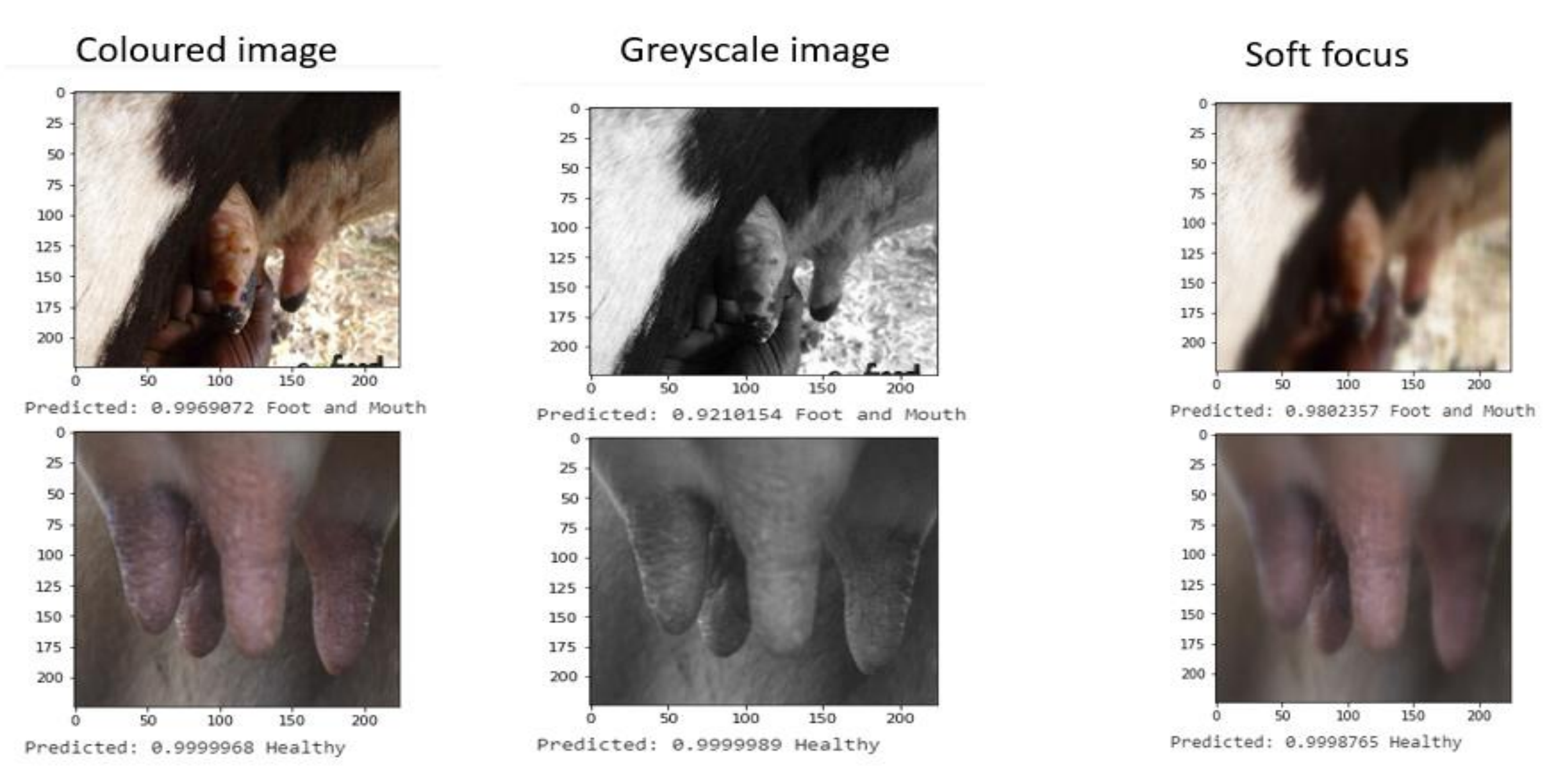
Prediction of gum lesion and non-gum lesion images



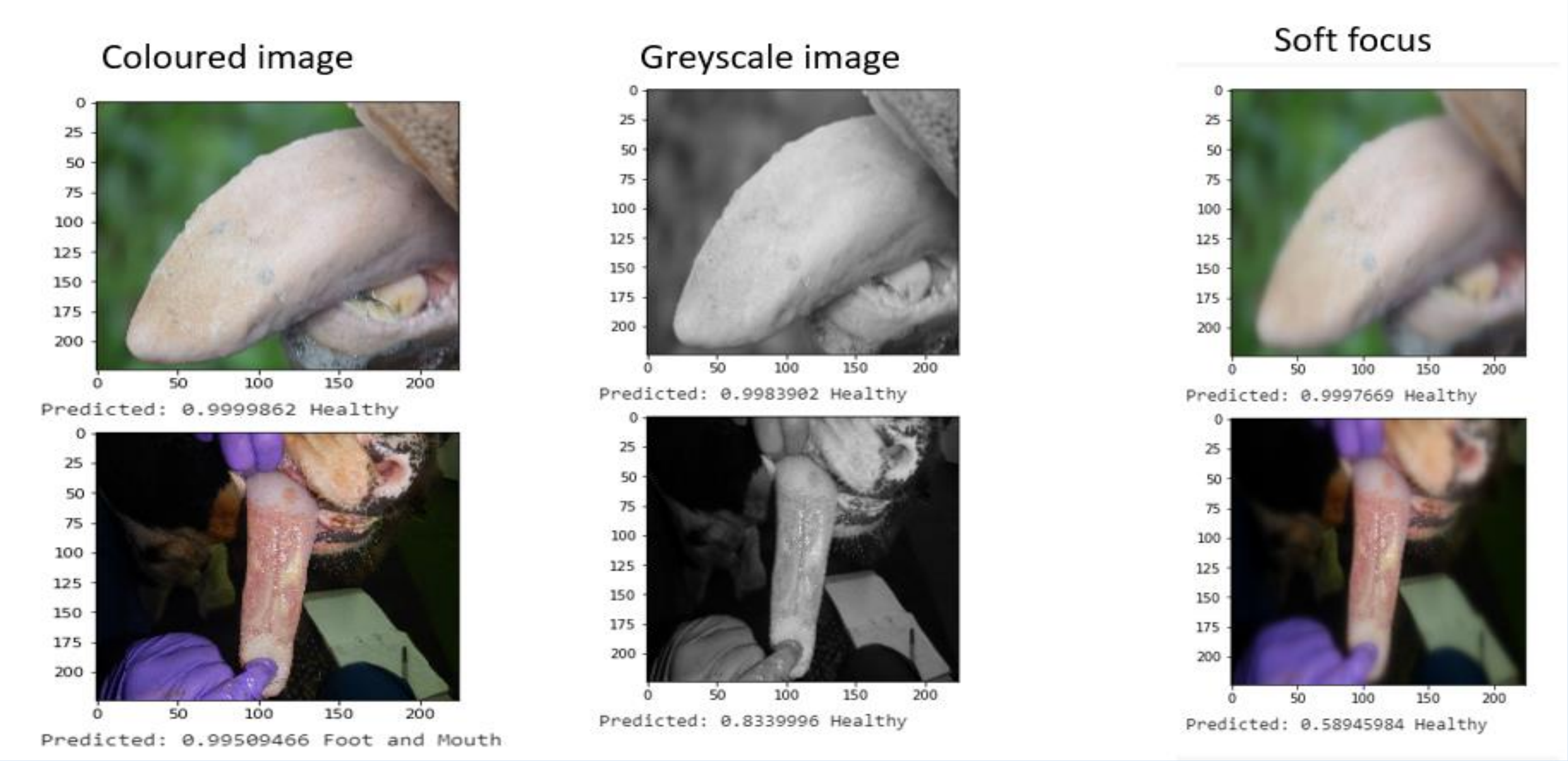
Prediction of drooling and non-drooling image



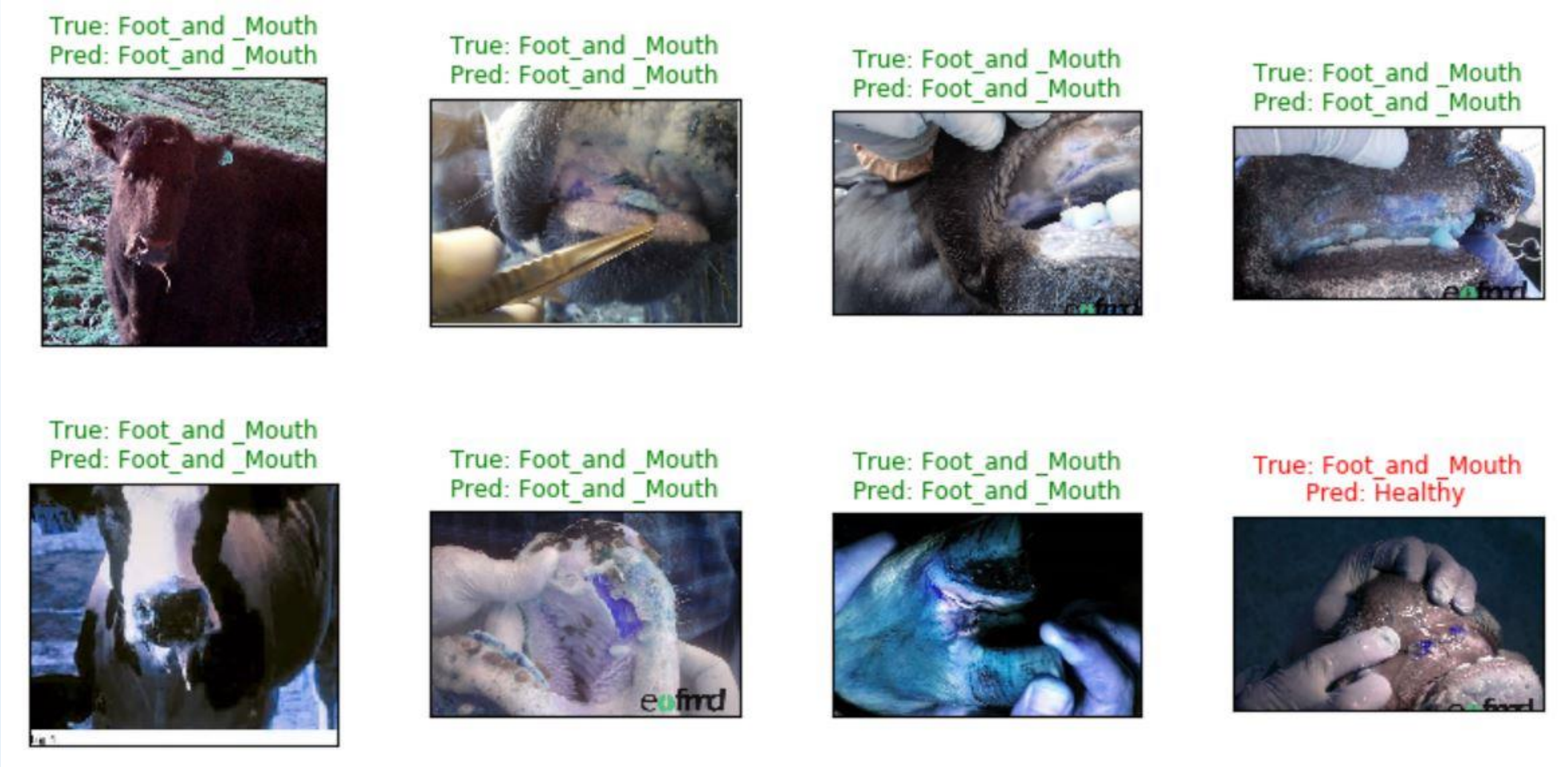
Prediction of teat lesion and non-lesion



Prediction of Tongue lesion and non-tongue lesion



Batch testing



Conclusion

- This study set out to evaluate how effective is the detection of FMD using different deep learning architectures
- Findings of this study’ show that FMD can be detected using deep learning however larger datasets of both FMD and healthy images are required to improve the performance evaluation metrics and also the identification of the disease
- Thus veterinary departments and international organisations across the World must be encouraged to take images and archive of cattle diseased with FMD.
- The main contribution of this study is that it has set the groundwork for the development of a mobile application (app) that will be used for the detection of FMD.

Acknowledgements

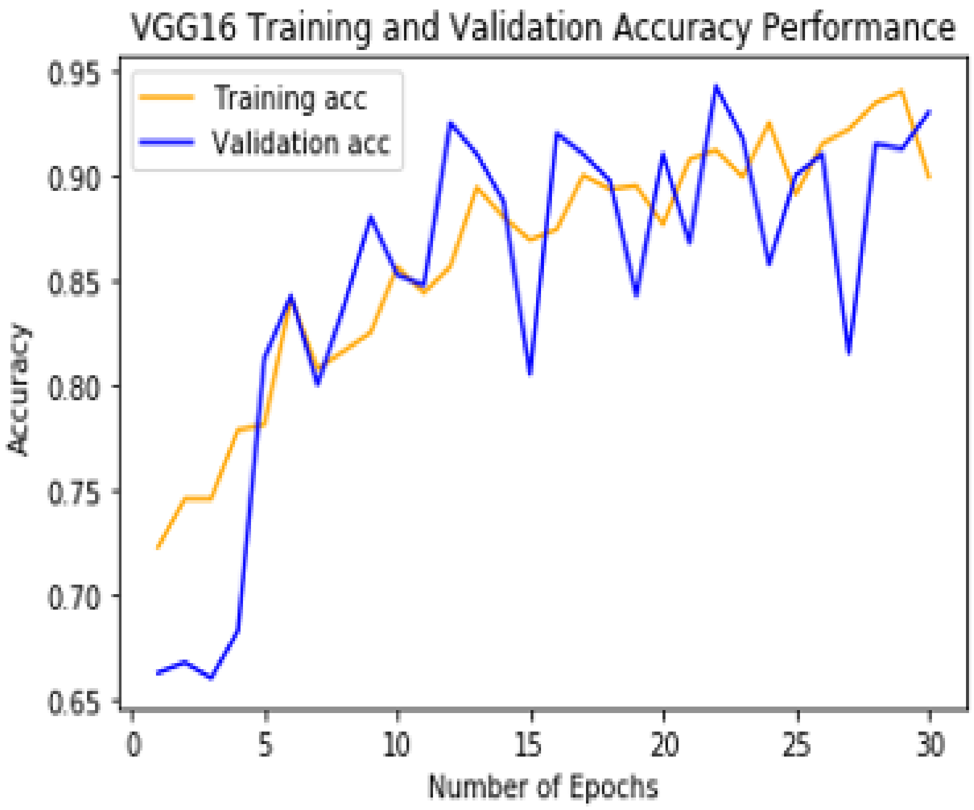
- I give my gratitude to all the authors who were involved in the contribution of the articles and journals that contain information related to my project.

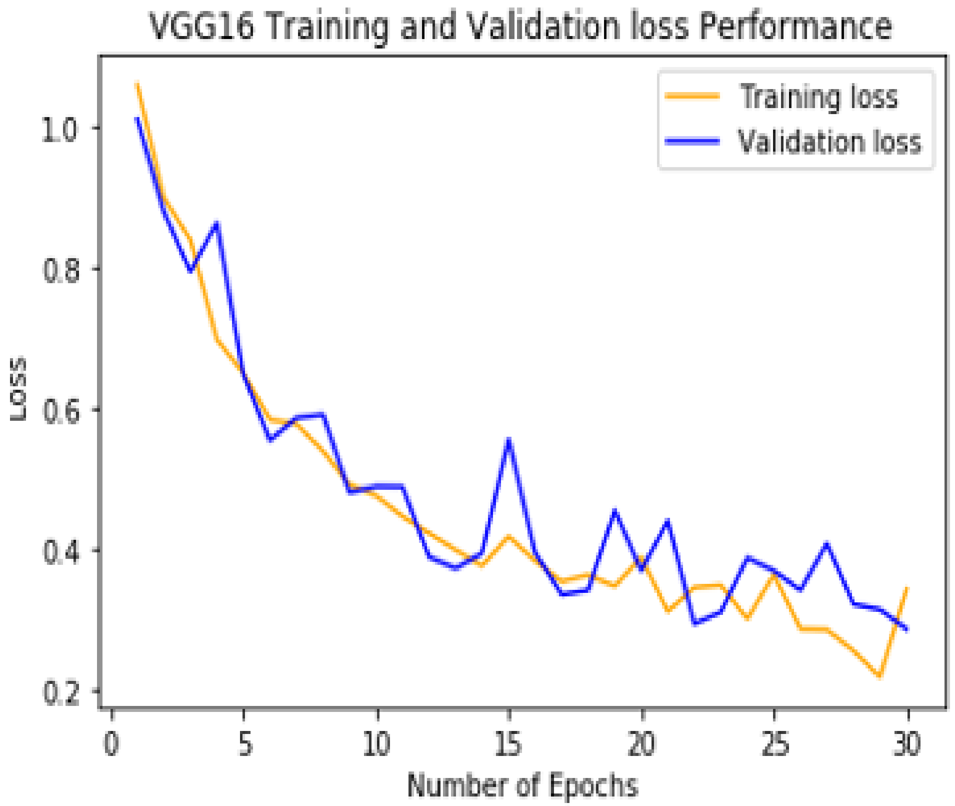
- I also thank my supervisor, Dr. Marisa, for helping me through to complete my project. I would also like to thank Dr M Munochiveyi for his important comments and review of this study.

- I would also like to extend my gratitude to the European Union Foot and Mouth division and Pirbright Institute for providing the foot and mouth diseased images.

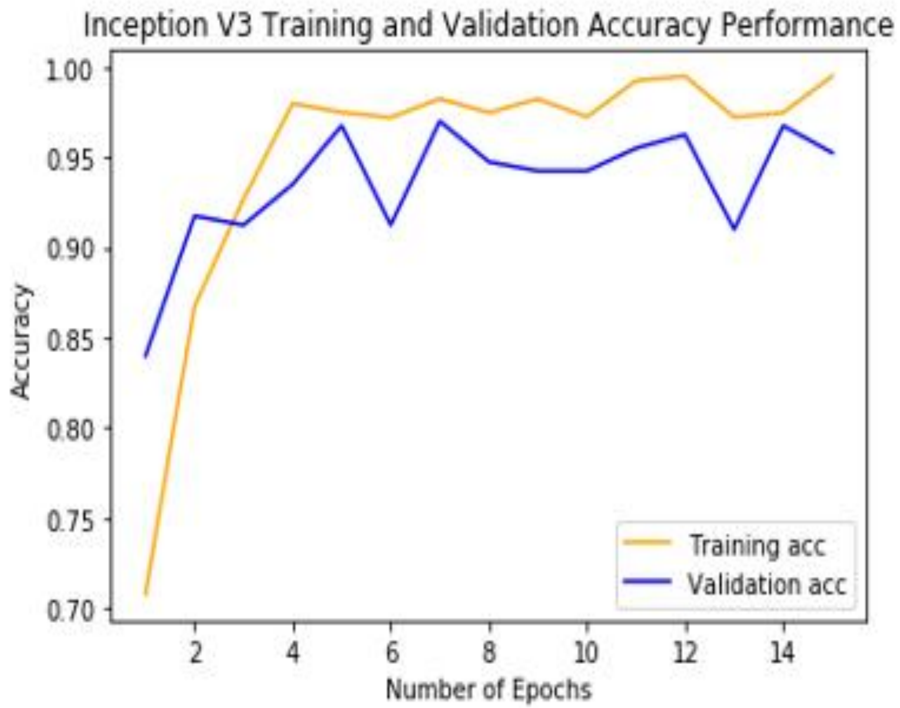
- The staff of the University of Zimbabwe farm in Mazowe played a major role in the acquisition of healthy images as they helped in the preparation of cattle for images to be taken.

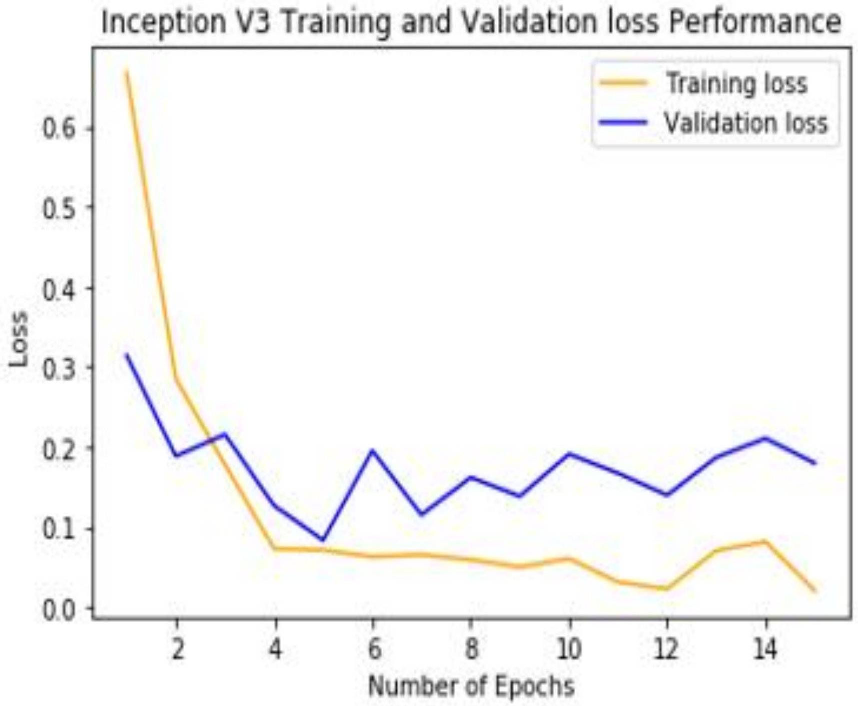
VGG-16 Accuracy and loss performance



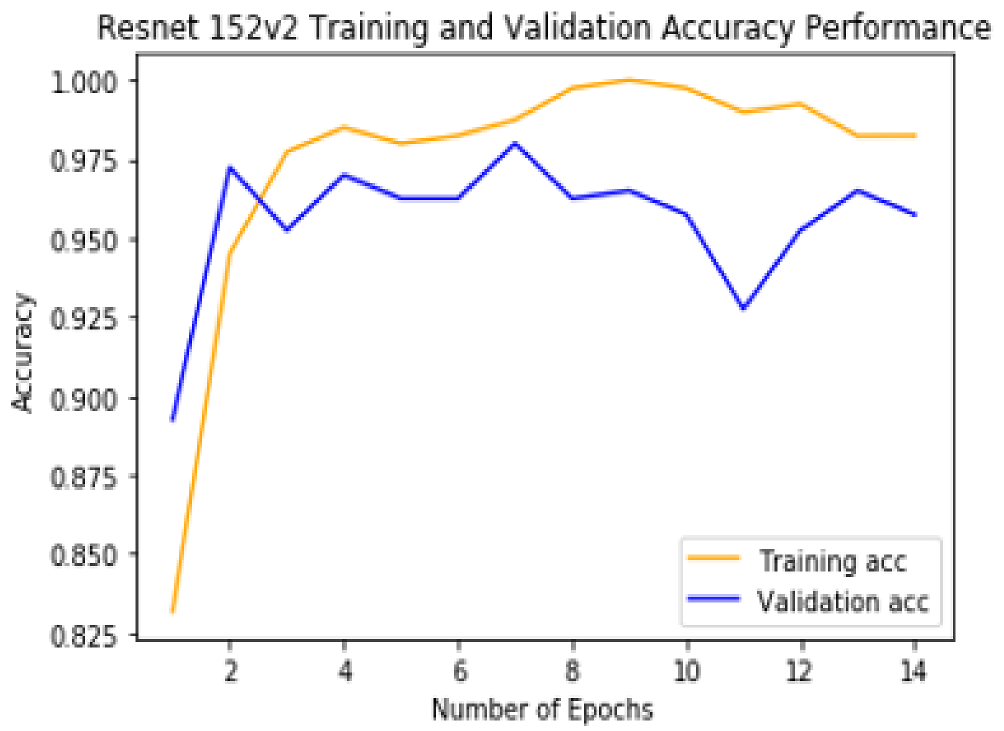


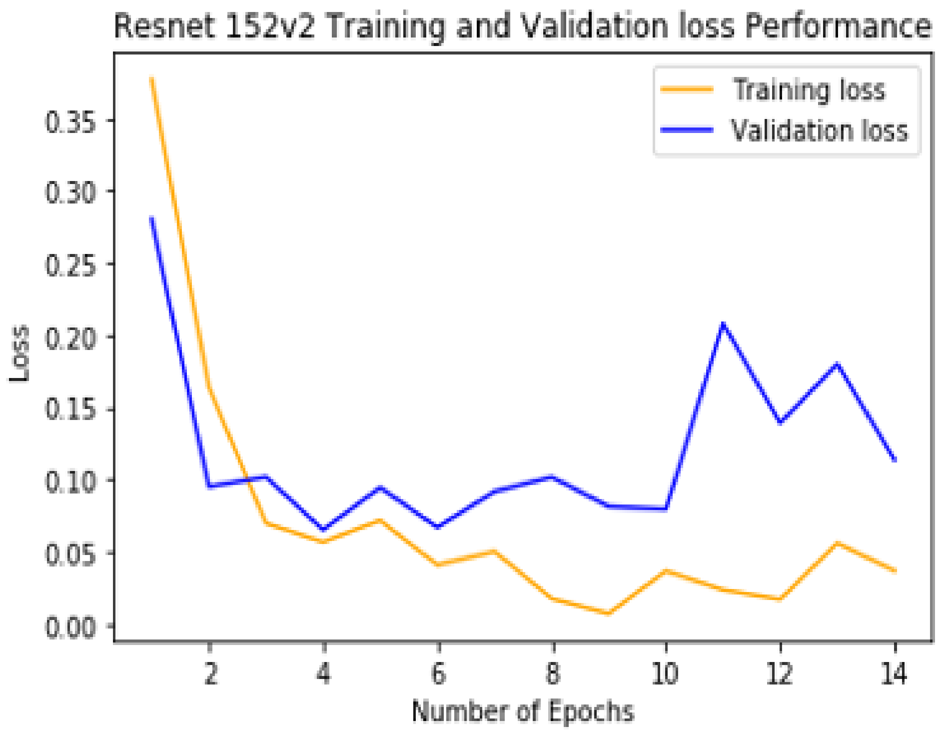
Inception v3



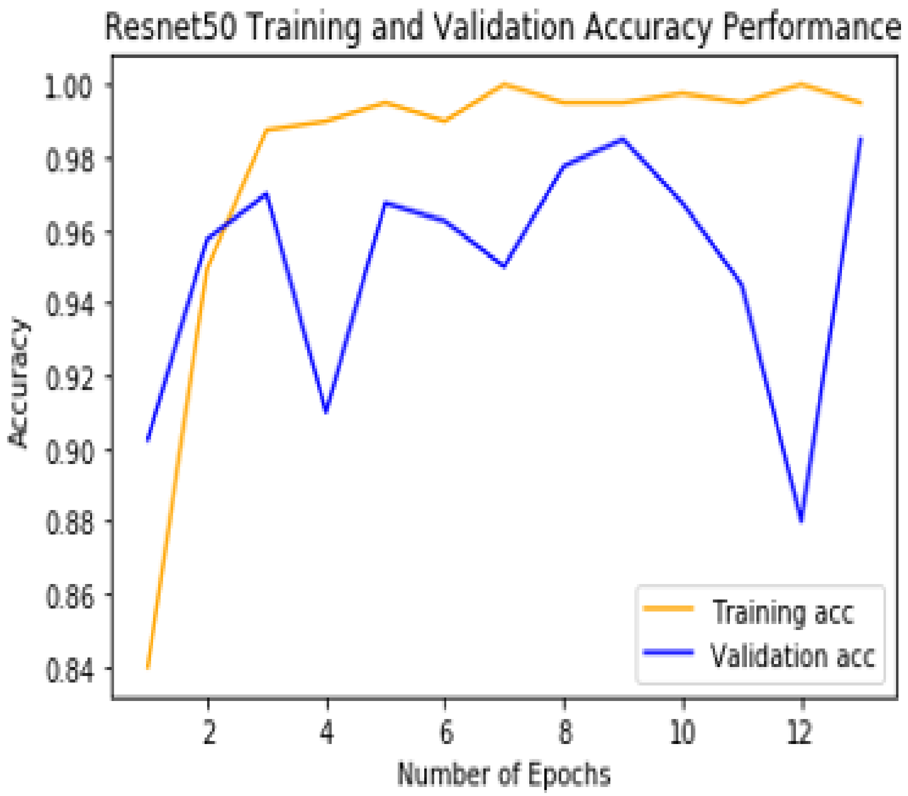


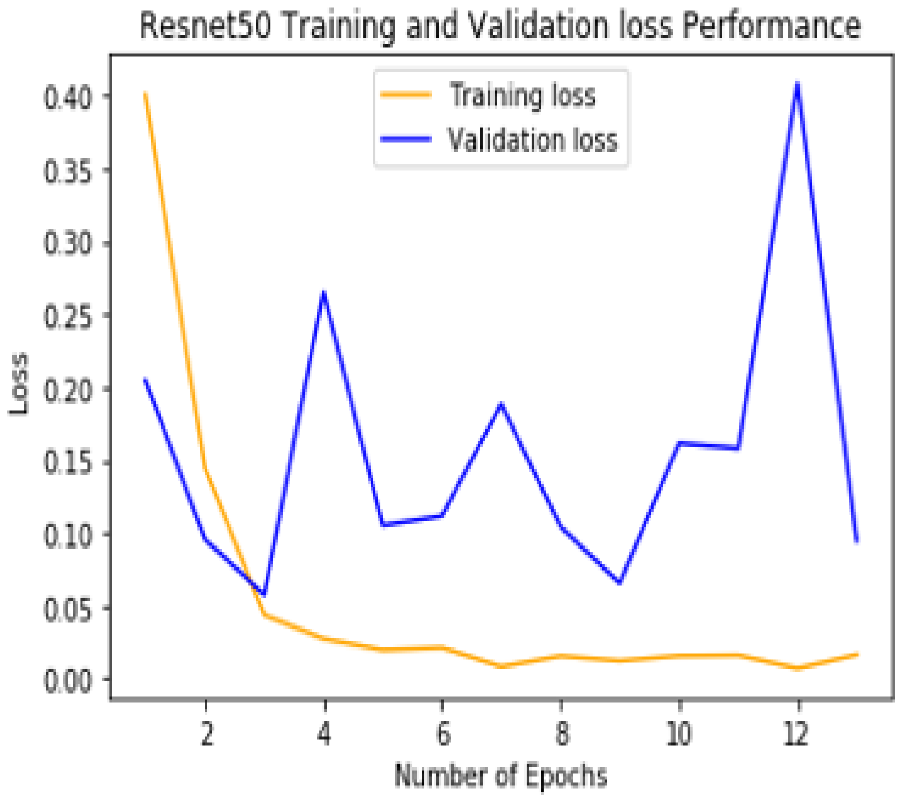
ResNet 152v2



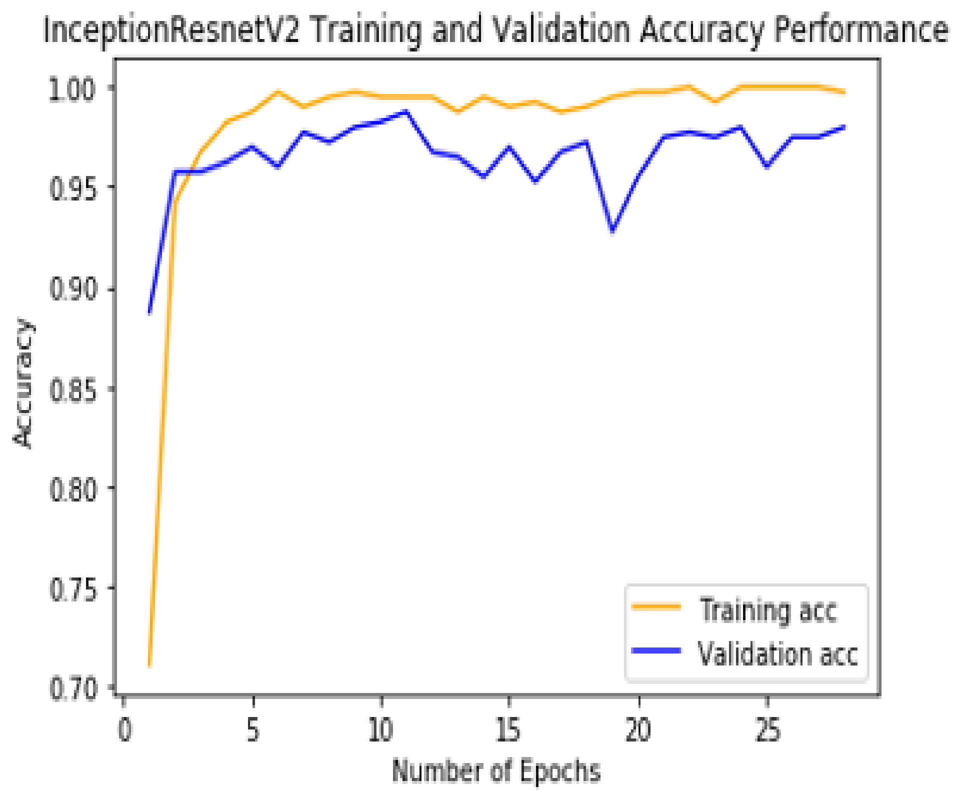


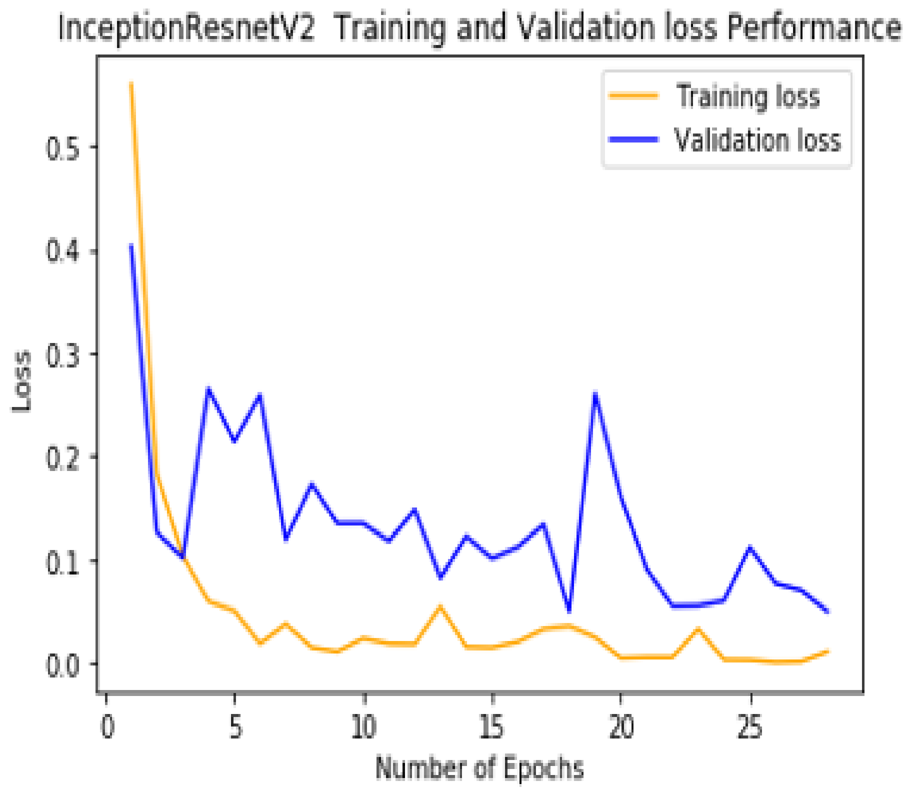
ResNet 50


Resnet50 Training and Validation Accuracy Performance
Accuracy
1.00
0.98
0.96
0.94
0.92
0.90
0.88
0.86
0.84
2
4
6
8
10
12
Number of Epochs
Training acc
Validation acc


Resnet50 Training and Validation loss Performance
Loss
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
2
4
6
8
10
12
Number of Epochs
Training loss
Validation loss

InceptionResnetv2





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