

# Low-cost machine learning algorithms to predict growth and carcass traits in pigs

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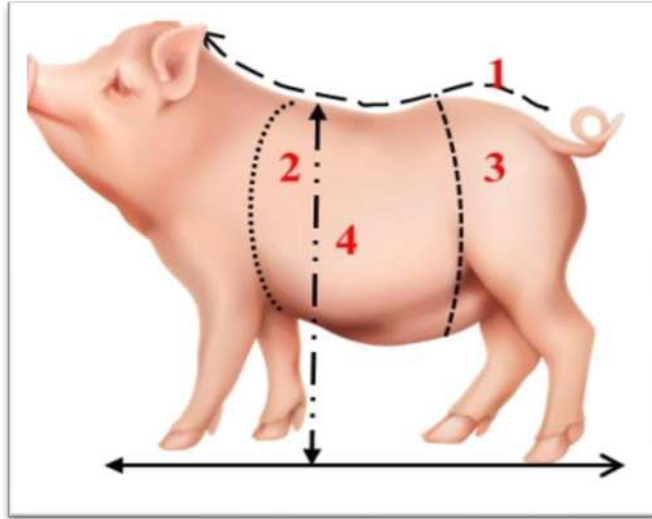


**AG2PI**  
Agricultural Genome to  
Phenome Initiative

# Introduction



Direct measurement



Key point measurement



Ultrasound (Back Fat and Loin Depth)

# Introduction

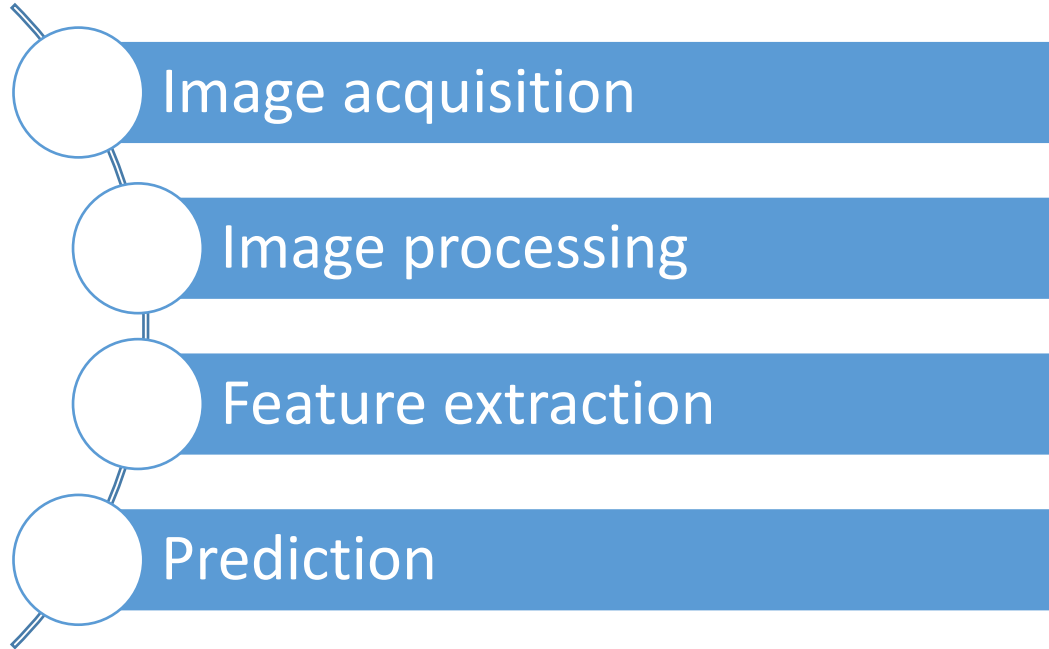
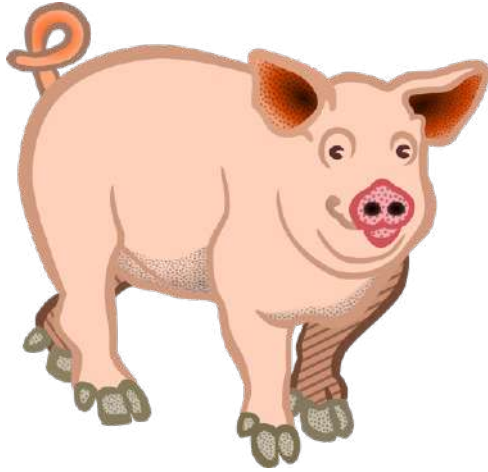
## ❖ Objective

- ❖ Develop a low-cost machine learning pipeline based on 2D images to predict
  - ❖ Body weight
  - ❖ Backfat thickness
  - ❖ Loin depth

## ❖ Benefits

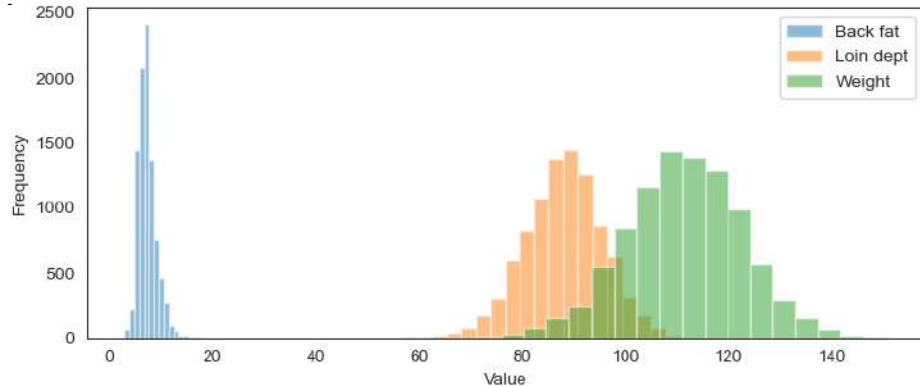
- ❖ Less time-consuming
- ❖ More cost-effective
- ❖ Tracks daily gains, nutritional status, and health performance
- ❖ Contributes to breeding and genetic management programs

# Outline of Materials and Method



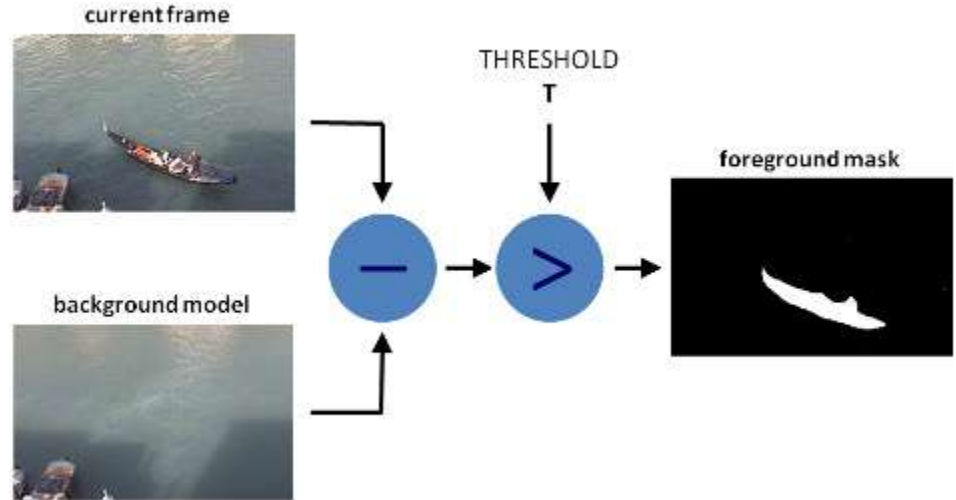
# Image acquisition – by PIC

- ❖ Uncontrolled 2-D side view of pigs
- ❖ Recorded 9K individuals at 60 frames per second
- ❖ Average recording duration was 7.19 seconds
  
- ❖ Measurements taken for each individual:
  - ❖ Body weight (WT)
  - ❖ Backfat thickness (BF)
  - ❖ Loin depth (LD)



Distribution of body weight, back fat, and loin depth

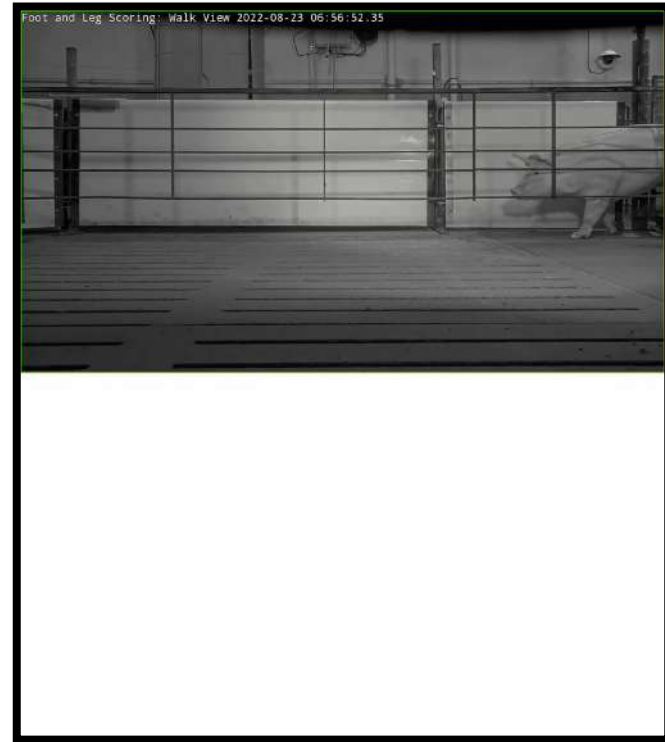
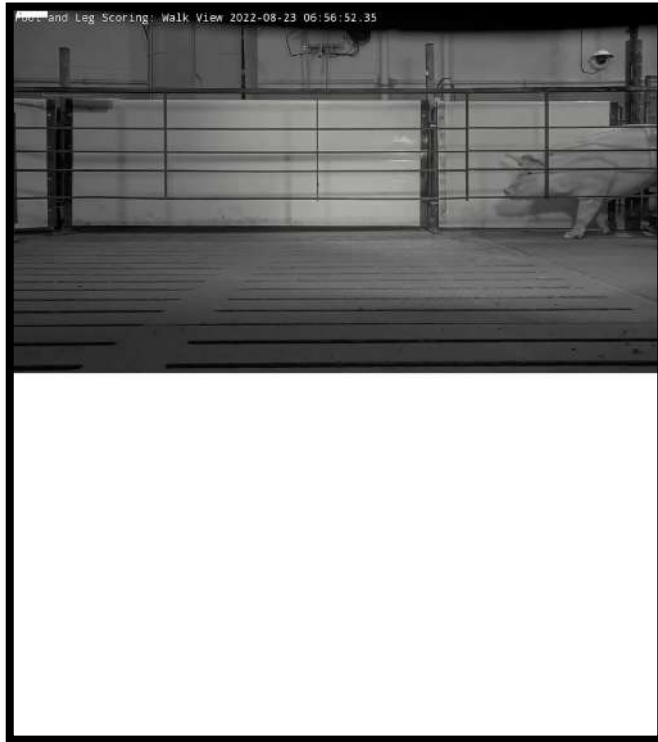
# Image processing: body segmentation (OpenCV)



Background/foreground segmentation using OpenCV

[https://docs.opencv.org/3.4/d1/dc5/tutorial\\_background\\_subtraction.html](https://docs.opencv.org/3.4/d1/dc5/tutorial_background_subtraction.html)

# Image processing: body segmentation (OpenCV)



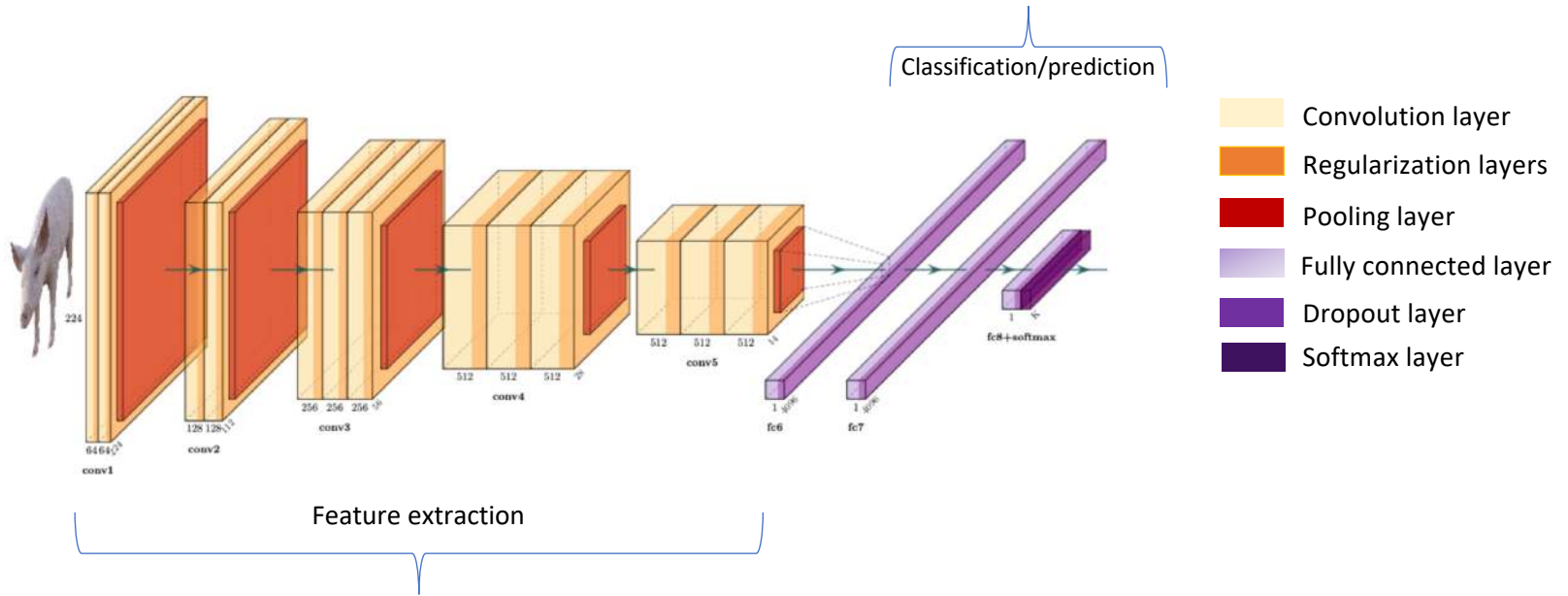
# Image processing: body segmentation (deep learning)



Illustration of a corner case handled by deep learning



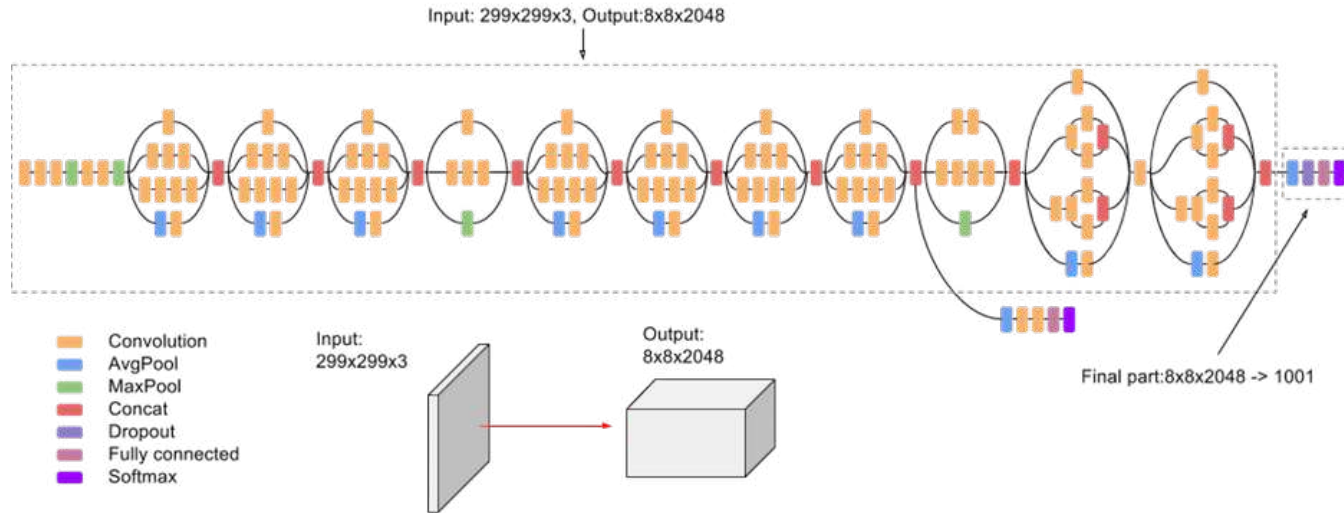
# Feature extraction: VGG16



Feature extraction using pretrained VGG16

<https://github.com/HarisIqbal88/PlotNeuralNet/tree/maste>

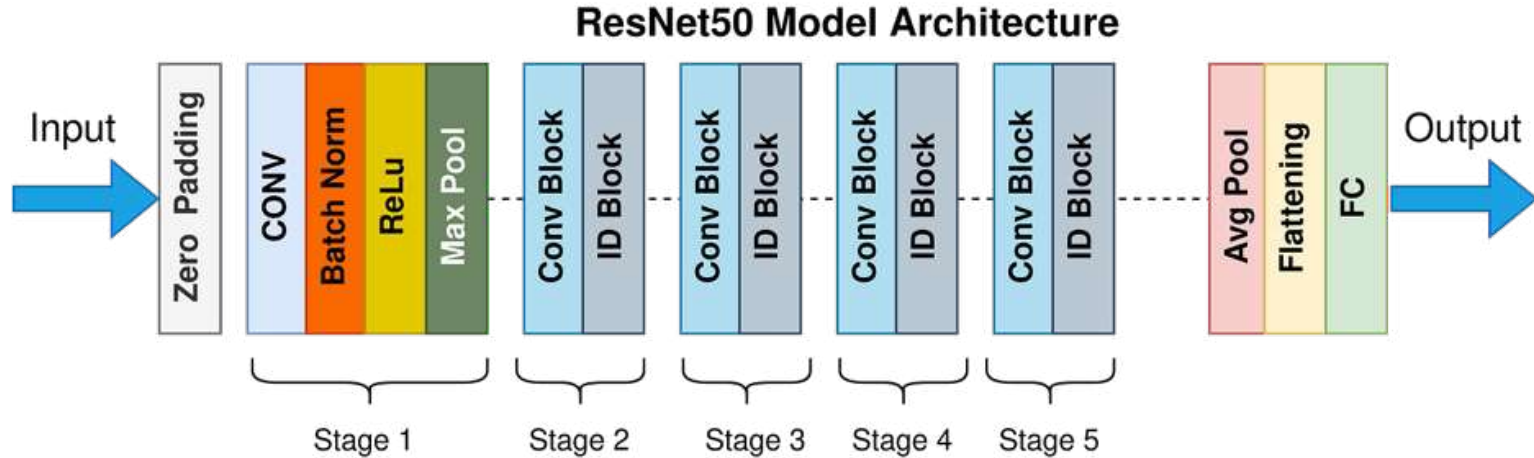
# Feature extraction: InceptionV3



Feature extraction using pretrained InceptionV3

<https://cloud.google.com/tpu/docs/inception-v3-advanced>

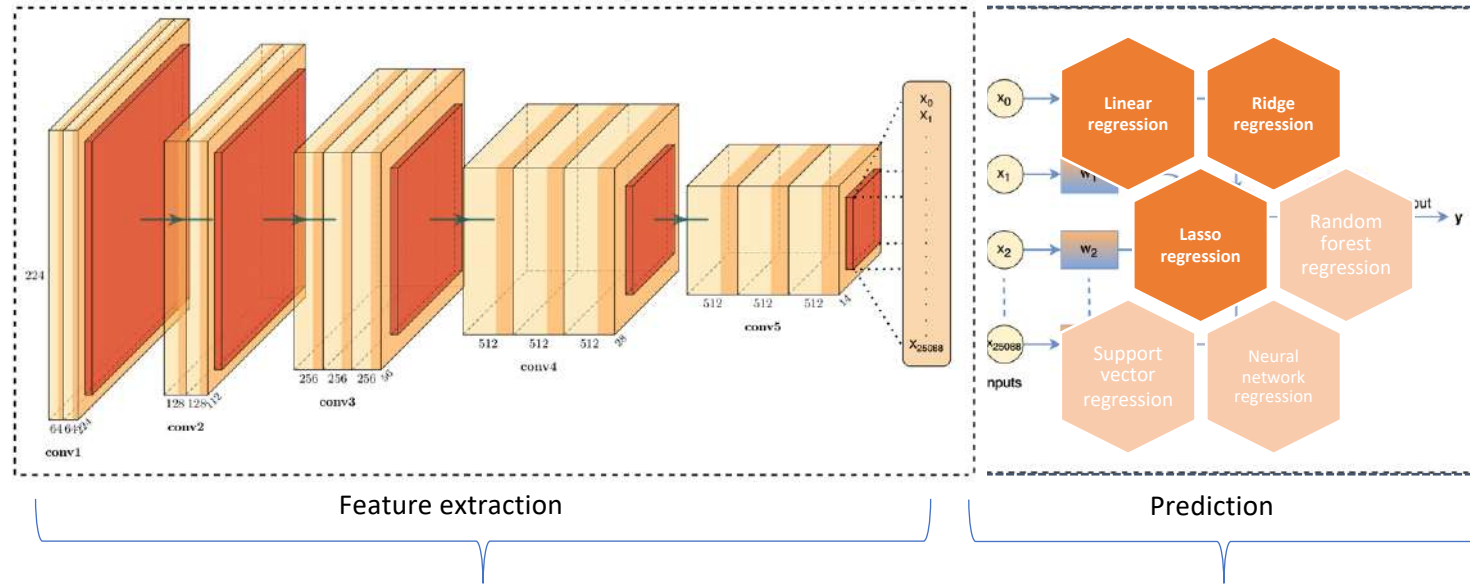
# Feature extraction: ResNet50



Feature extraction using pretrained ResNet50

<https://doi.org/10.3390/diagnostics12081853>

# Prediction: overview



# Prediction: cost function

Linear regression

$$\sum_{i=1}^M (y_i - \hat{y}_i)^2 = \sum_{i=1}^M \left( y_i - \sum_{j=0}^N \beta_j * x_{ij} \right)^2$$

Lasso regression

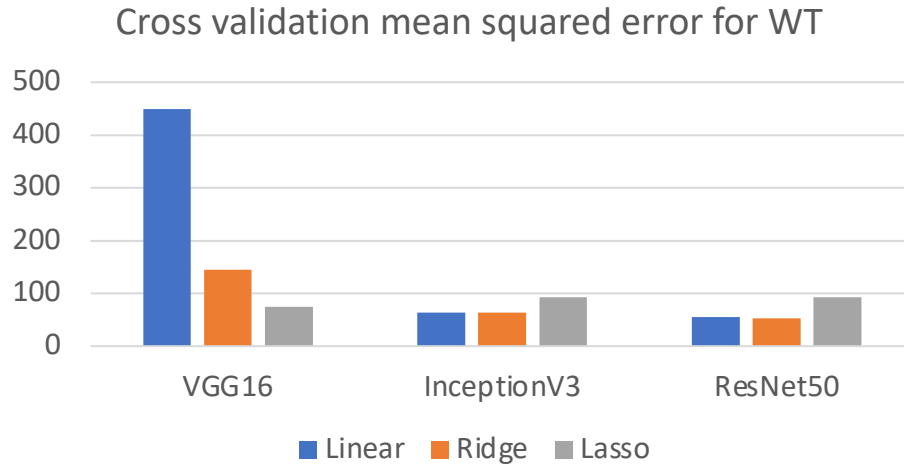
$$\sum_{i=1}^M (y_i - \hat{y}_i)^2 = \sum_{i=1}^M \left( y_i - \sum_{j=0}^N \beta_j * x_{ij} \right)^2 + \lambda \sum_{j=0}^N |\beta_j|$$

Ridge regression

$$\sum_{i=1}^M (y_i - \hat{y}_i)^2 = \sum_{i=1}^M \left( y_i - \sum_{j=0}^N \beta_j * x_{ij} \right)^2 + \lambda \sum_{j=0}^N \beta_j^2$$



# Results: model selection

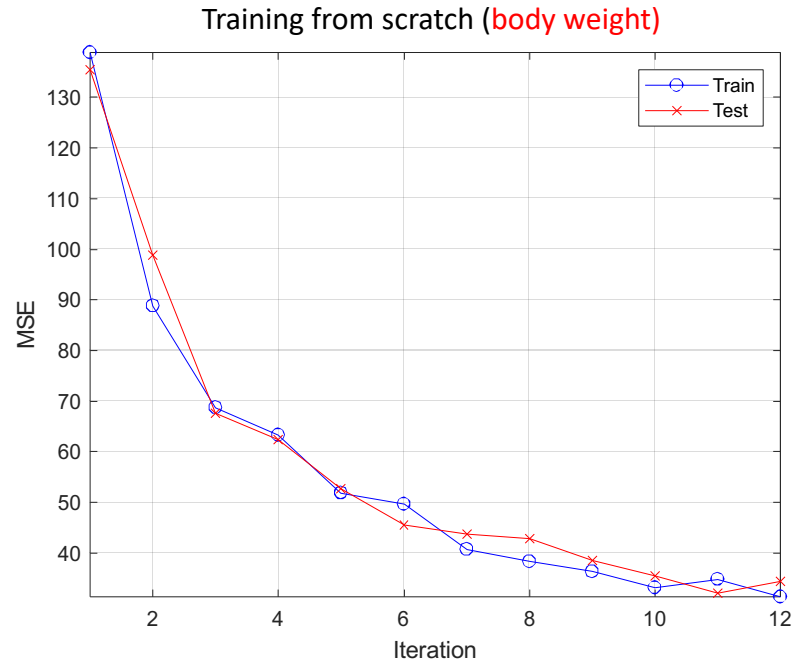
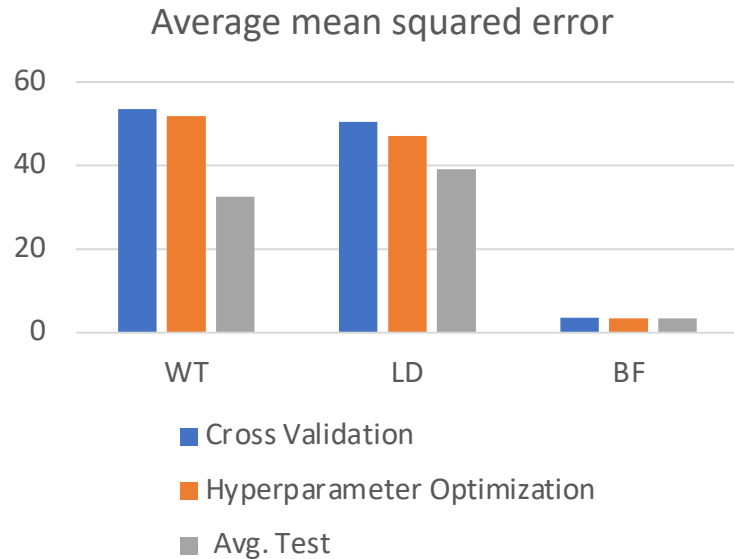


➤ Body Weight -> ResNet50 + Ridge

➤ Loin Depth -> ResNet50 + Ridge

➤ Back Fat -> ResNet50 + Ridge

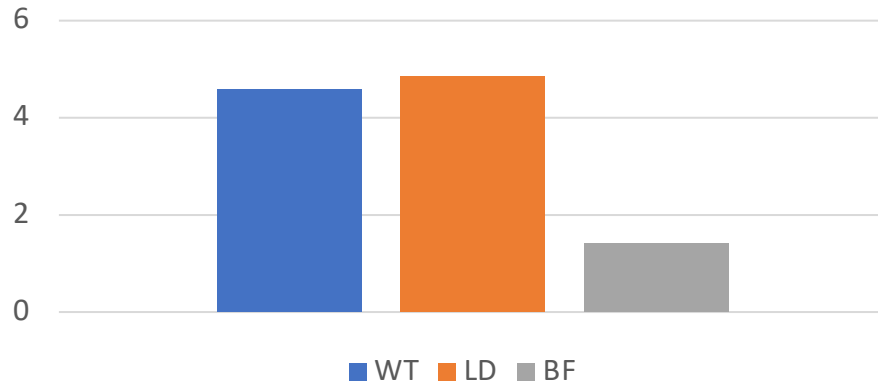
# Results: prediction accuracy



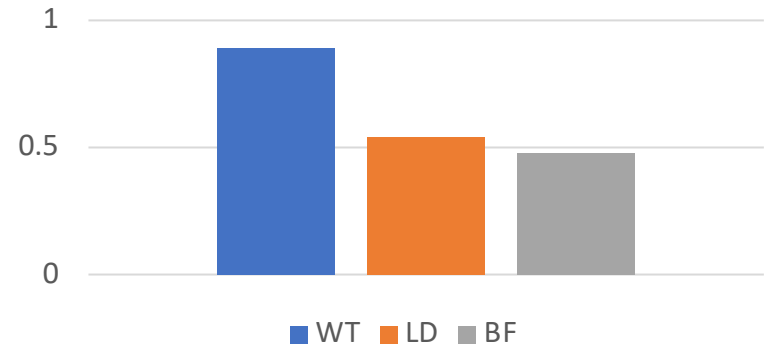
Source: Eric Psota, talk at AGBT-Ag 2024

# Results: prediction accuracy

Mean absolute error

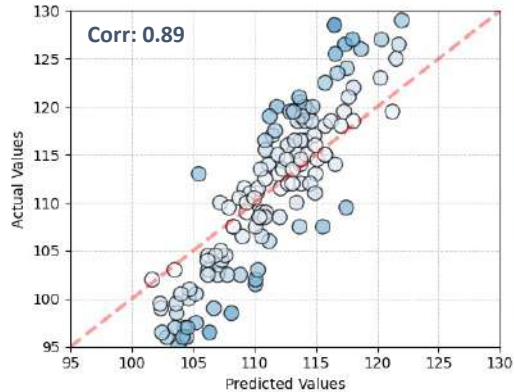


Correlation between actual and predicted

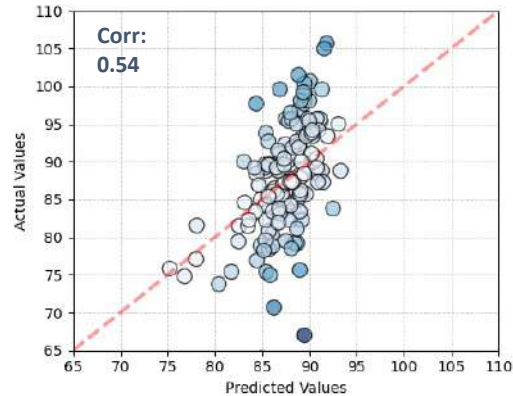




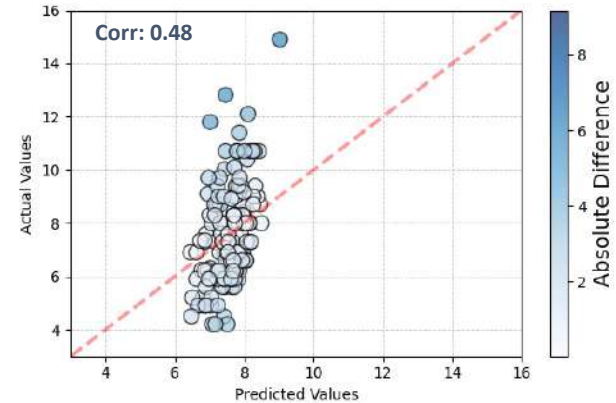
# Results: actual vs predicted



Predicted average **body weight**  
for each individual



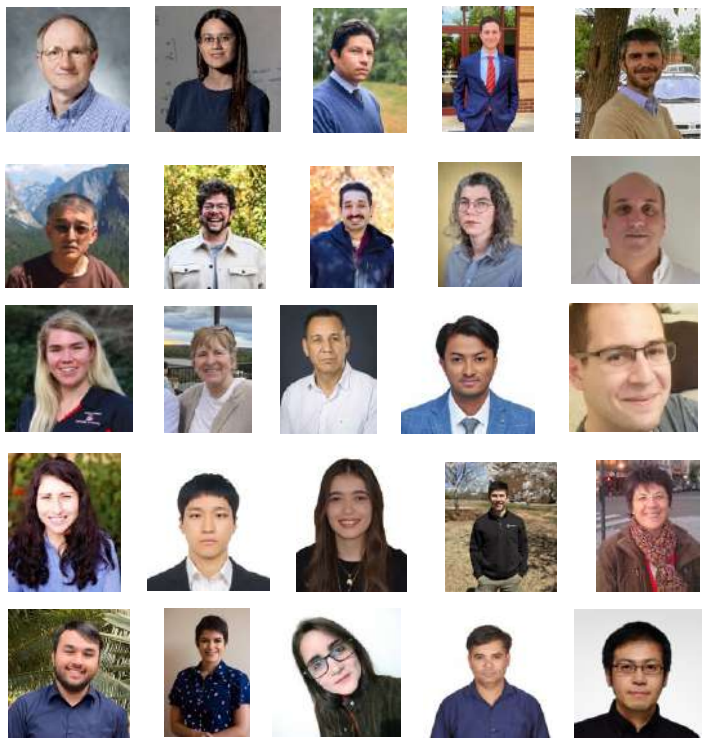
Predicted average **loin depth**  
for each individual



Predicted average **back fat**  
for each individual

# Conclusions

- ❖ Many previous studies were limited in quality, variability, and dataset size
- ❖ Employed various deep learning approaches to extract features
- ❖ Applied different regression models to predict outcome
- ❖ Pre-trained deep learning model can efficiently extract meaningful features
- ❖ Enable large-scale digital phenotyping
- ❖ In our future work, we will use the extracted features for genomic predictions



# Acknowledgements

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**Thank you!**