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CENTER FOR QUANTITATIVE GENETICS AND GENOMICS

QGG

Innovative phenotyping systems to advance selective breeding in black soldier fly

Grum Gebreyesus

EAAP · EUROPA · EAZ · EVT · FEZ

INSECT GENETICS IMProvement IMPlementation IMPact

Center for Quantitative Genetics and Genomics

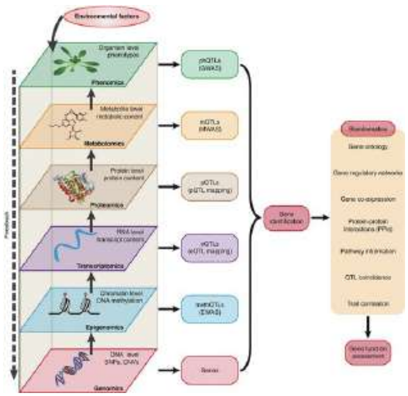
Animal genetics

Plant genetics

Human genetics

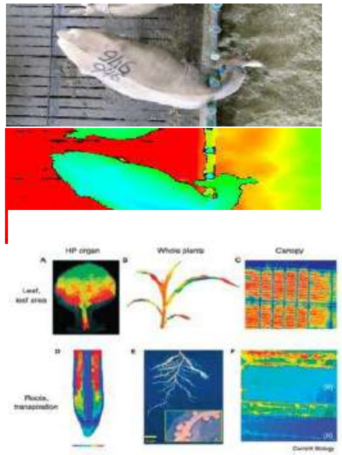
Scientific focus areas

Integrative genomics and bioinformatics



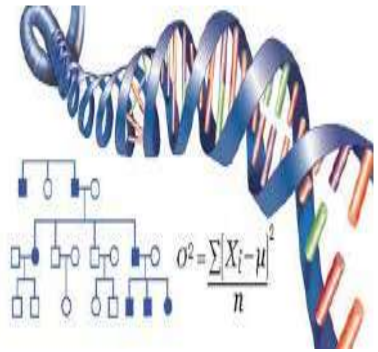
Basic understanding of regulation of traits: Genome, epigenetics, Gene expression, proteome, metabolome, mikrobiome, phenome

Digitalisation and phenomics



Automatised assesment of phenotypes (animal/ plant/field) by image, video, sensors, .. And use of ML/AI algorithms

Statistical and quantitative genetics

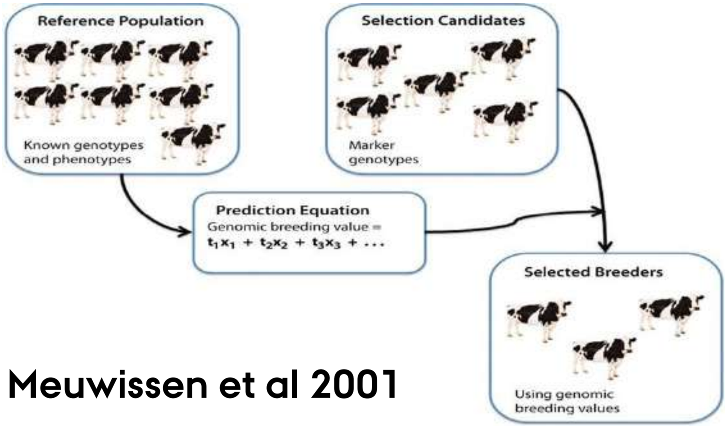


Method/software development, genetic parameters, genomic prediction, data integration

Population genetics and breeding plans

- Breeding and breed conservation programs
- Balanced breeding goal/objective, while minimizing inbreeding and maintaining genetic diversity

Genomic selection



Meuwissen et al 2001

Research | Open access | Published: 27 January 2010

Genomic prediction when some animals are not genotyped

Ole F Christensen & Mogens S Lund

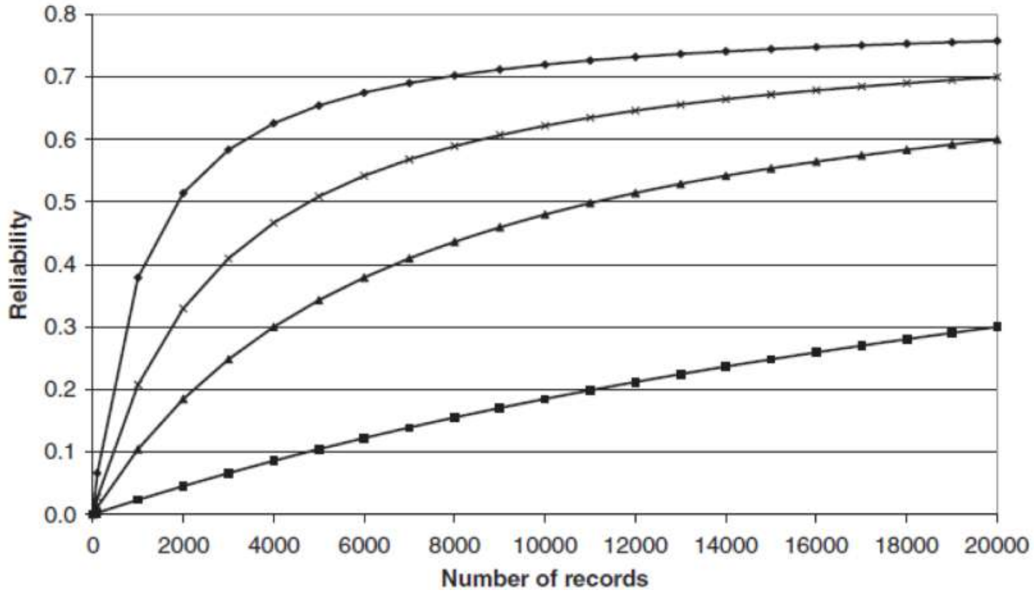
A relationship matrix including full pedigree and genomic information

A. Legarra,*[1] I. Aguilar,†‡ and I. Misztal†
*INRA, UR631 SAGA, BP 52627, 32326 Castanet-Tolosan, France
†Department of Animal and Dairy Science, University of Georgia, Athens 30602

Genomic Selection in the Nordic Countries

M. S. Lund[1] and G. Su[1]
[1]Aarhus University, Faculty of Agricultural Sciences, Genetics and Biotechnology, Foulum, Denmark.

Phenotype



heritability of 0.03 (■), 0.15 (▲), 0.35 (X) and 0.90 (◆).

Research News

Phenotype is king, researchers say, after 20 family members have condition misdiagnosed

BMJ 2016 ; 355 doi: https://doi.org/10.1136/bmj.i5884 (Published 02 November 2016)

Anim Front. 2020 Apr; 10(2): 19–22.
Published online 2020 Apr 1. doi: 10.1093/af/vfaa004

Dairy cows: in the age of the genotype, #phenotypeisking

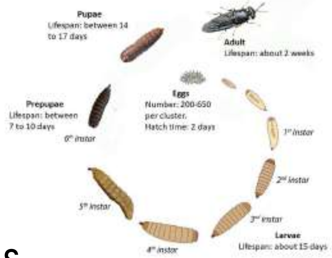
Mike Coffey

Phenotyping: main bottleneck in insect breeding

Conventional methods unsuitable
- Small individual size limits measurements.
- Metamorphic lifecycle complicates linking traits across stages.
- Short lifecycle restricts observation time.

Production system limitations
- High-density rearing hinders individual tracking.
- Bulk and vertical farming reduce accessibility for monitoring.
- Controlled environments (climate, lighting)

Technological bottlenecks
- Lack of real-time automated phenotyping systems.
- Challenges in tracking individual performance within mass-reared population.



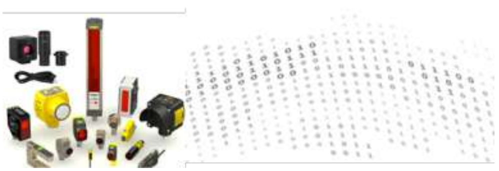
Digitalization in agriculture

Advancements

Data

Algorithm

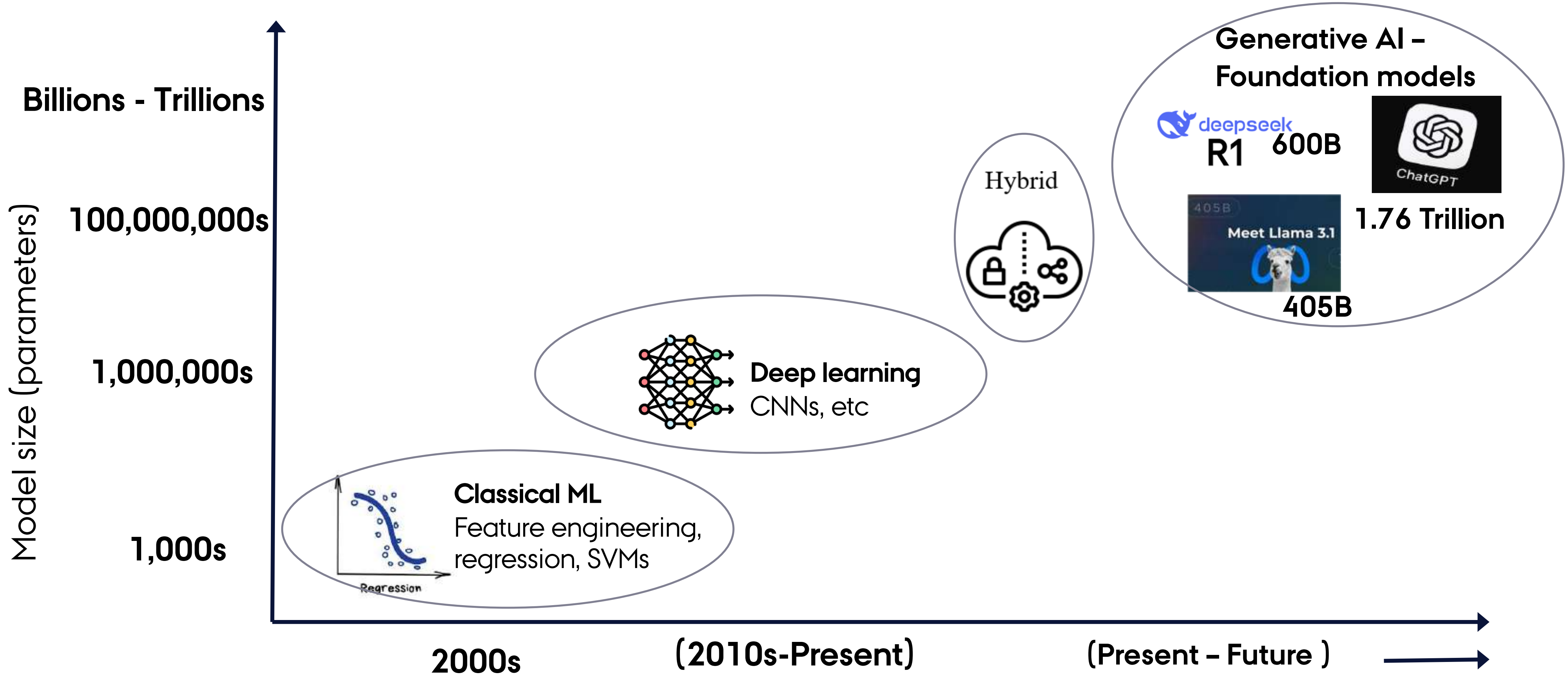
Compute



Data - Sensors

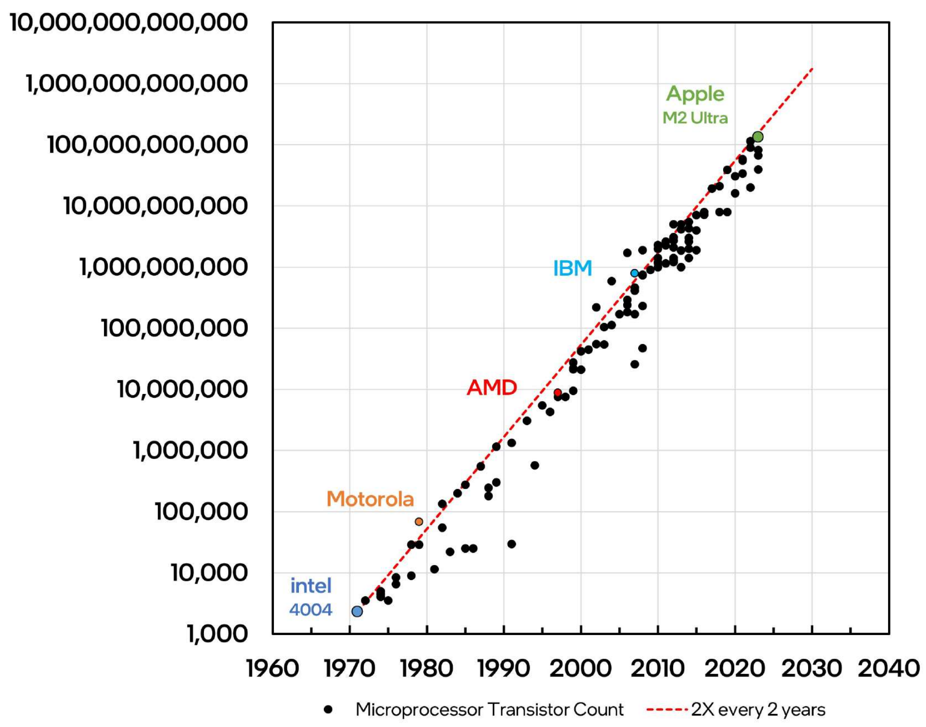
- Realtime high throughput data recording systems; sensors
  - Image
  - Motion
  - Sound
  - Chemical composition (Spectroscopy)

Algorithm

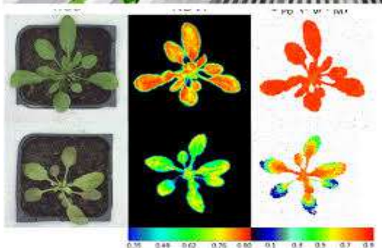

Billions - Trillions
100,000,000s
1,000,000s
1,000s
Model size (parameters)
Generative AI –
Foundation models
deepseek
R1
600B
ChatGPT
1.76 Trillion
405B
Meet Llama 3.1
405B
Hybrid
Deep learning
CNNs, etc
Classical ML
Feature engineering,
regression, SVMs
Regression
2000s
(2010s-Present)
(Present – Future)

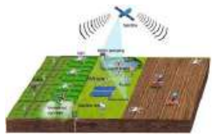
Compute

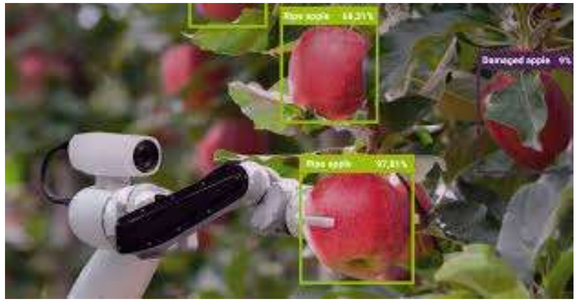
● Microprocessor Transistor Count ----- 2X every 2 years



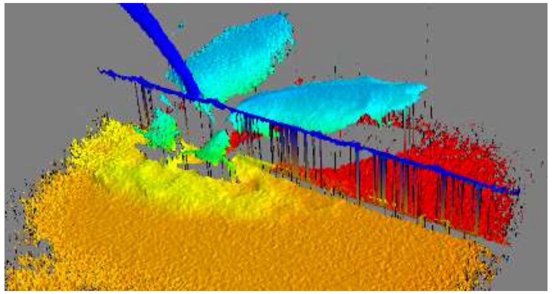
Application: Plant production

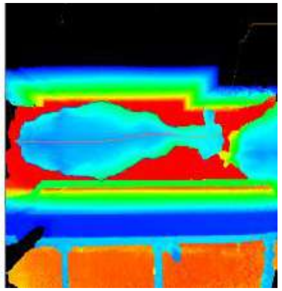




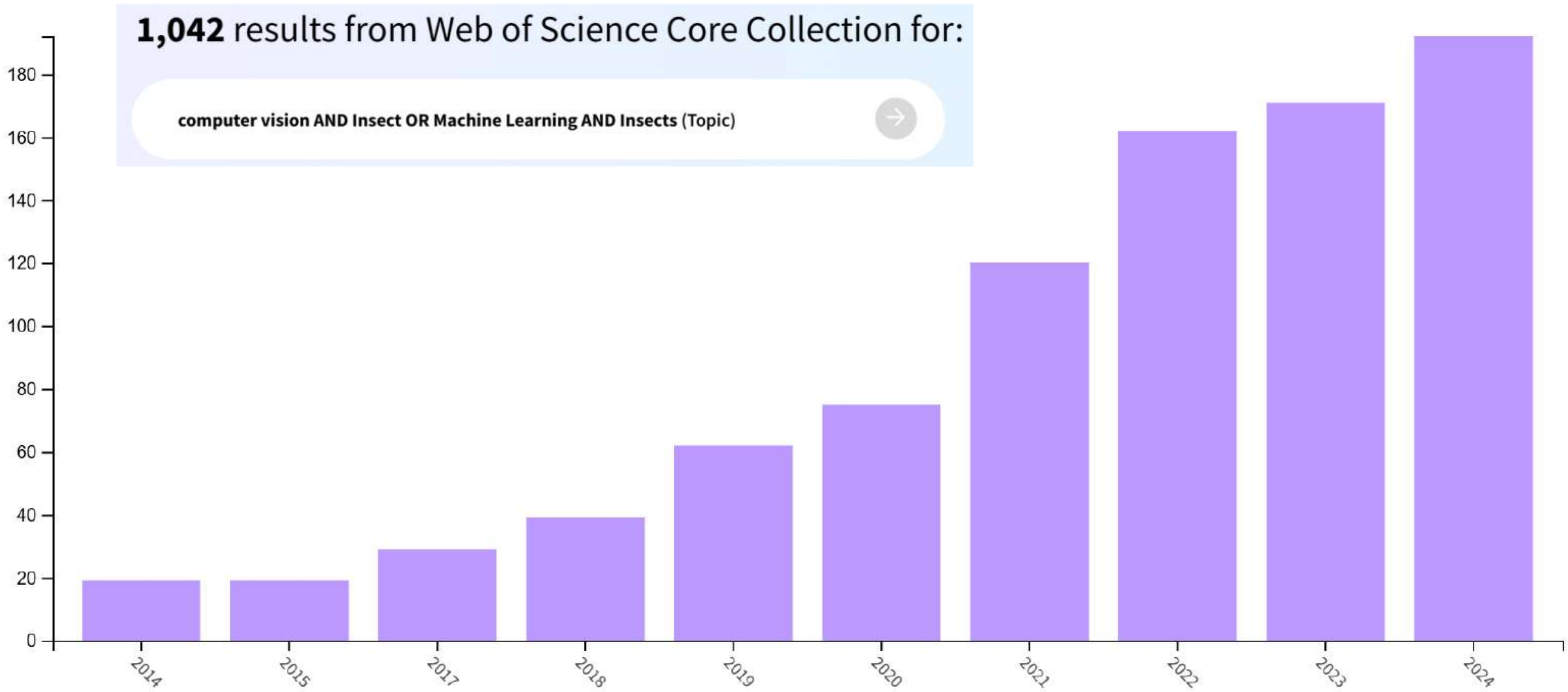


Applications: Livestock

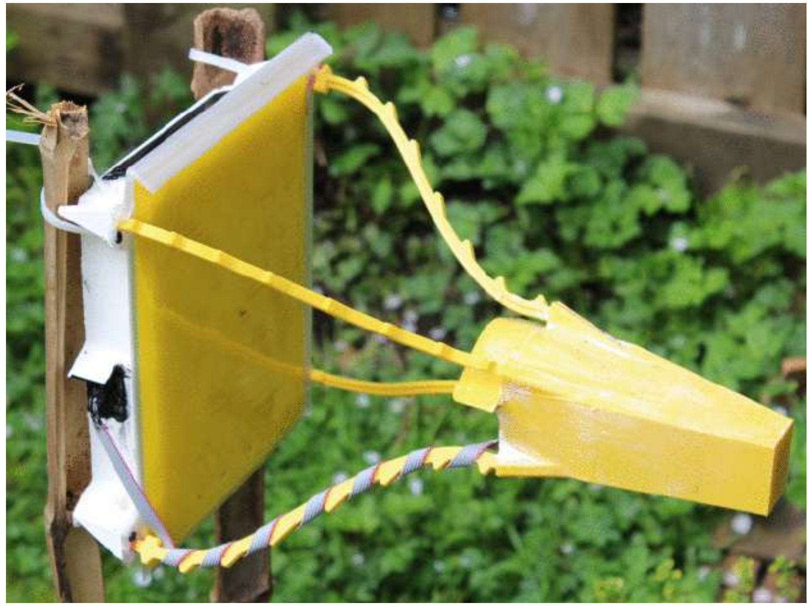




Applications: Insect



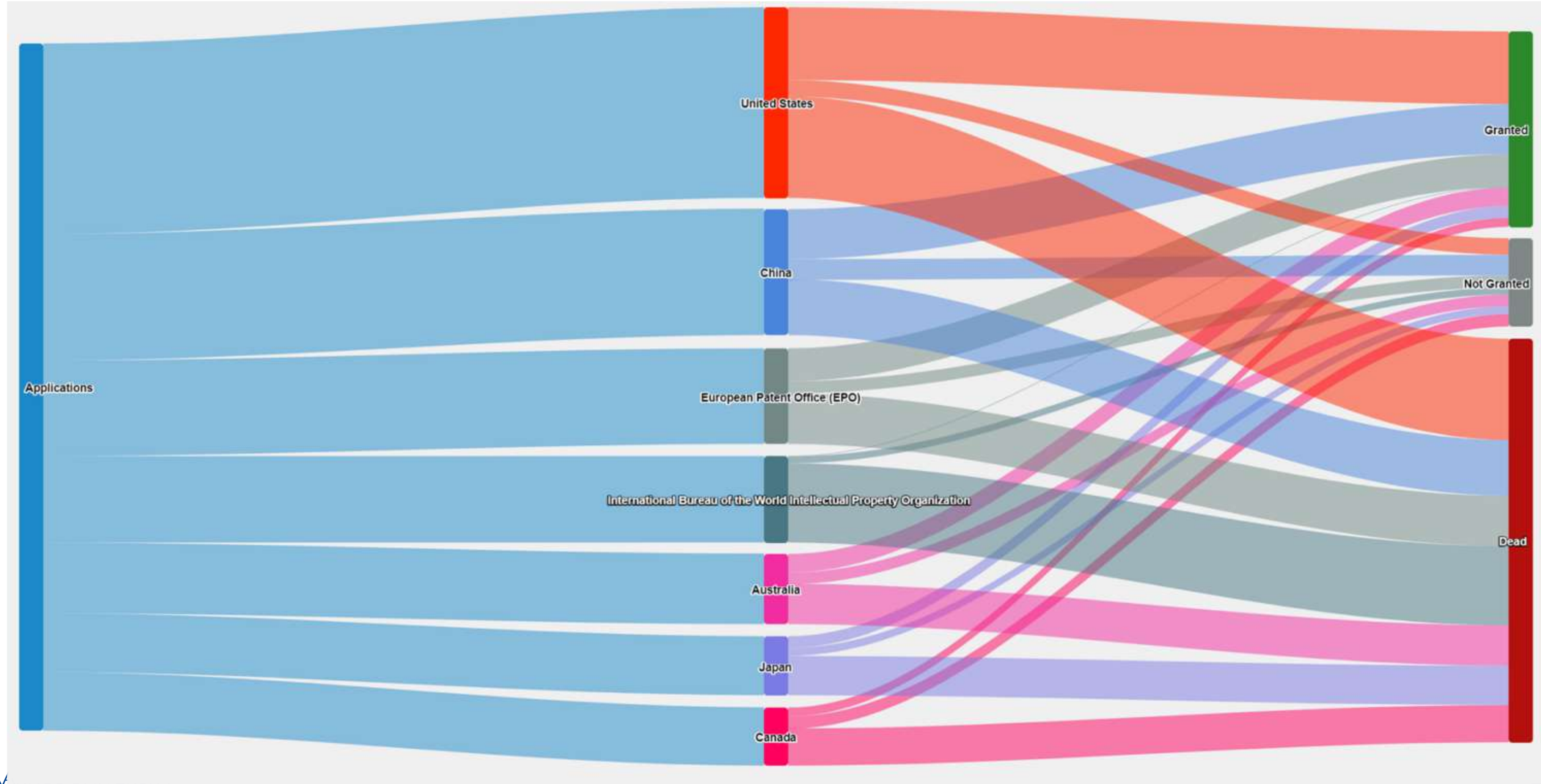
Research on insect applications



StickyPi (Geissmann et al. 2022)

Commercial solutions: Patent applications

Patent applications



Insect applications

Extensive research on the application of digital tools in insect studies

- Pest – plant interaction
- Ecology – biodiversity
- Taxonomy

Transferable knowledge to insect production for food & feed

Un-addressed unique needs for phenotyping

Behavioral and postural analyses establish sleep-like states for mosquitoes that can impact host landing and blood feeding

Oluwaseun M Ajayi [1,*], Justin M Marlman [1], Lucas A Gleitz [1], Evan S Smith [1], Benjamin D Piller [1], Justyna A Krupa [1], Clément Vinauger [2], Joshua B Benoit [1,*]

Article | Open access | Published: 27 September 2024

WingAnalogy: a computer vision-based tool for automated insect wing asymmetry and morphometry analysis

Shahab Eshghi, Hamed Rajabi, Natalia Matushkina, Lisa Claußen, Johannes Poser, Thies H. Büscher & Stanislav N. Gorb

Scientific Reports **14**, Article number: 22155 (2024) | Cite this article

Article | Open access | Published: 16 February 2022

Automating insect monitoring using unsupervised near-infrared sensors

Klas Rydhmer, Emily Bick, Laurence Still, Alfred Strand, Rubens Luciano, Salena Helmreich, Brittany D. Beck, Christoffer Grønne, Ludvig Malmros, Knud Poulsen, Frederik Elbæk, Mikkel Brydegaard, Jesper Lemmich & Thomas Nikolajsen

Phenotyping needs

Diverse – eco-relevance ←	**Target species & phenotypes**	→ *“Commercial” spp. & traits*
Few sample – “deeper” observations ←	*Scale & scope*	→ *Large-scale - routine*
Natural habitat or lab ←	*Environment*	→ *Industry scale production*

Phenotyping needs:

Value: useful & valuable

Platforms: non-destructive, non-invasive, non-intrusive

Measurement: accurate, precise, correlated to the "*True value*"

Scope: large scale, high throughput, cost effective (at the individual level)

Heritability analysis	$n = 10^2 - 10^3$
Correlations	$n = 10^3 - 10^5$
BV prediction	$n = 10^3 - 10^5$

Phenotyping needs:

Value: useful & valuable

- Efficiency
- Environment
- Resilience
- Production

Computer vision: Larval growth/size traits

Some studies on mealworm

Challenges in BSF application

- Non-rigid exoskeleton
- Tendency to change form and dimension when moving and in response to stimuli during imaging/sampling
- Image-based features might vary for the same individual

Multipurpose monitoring system for edible insect breeding based on machine learning

Paweł Majewski [1,✉], Piotr Zapotoczny [2], Piotr Lampa [3], Robert Burduk [1], Jacek Reiner [3]

▸ Author information ▸ Article notes ▸ Copyright and License information

PMCID: PMC9098436 PMID: 35551215

Noninvasive monitoring system for *Tenebrio molitor* larvae based on image processing with a watershed algorithm and a neural net approach

In: Journal of Insects as Food and Feed

Authors: A. Baur, D. Koch, B. Gatternig, and A. Delgado

Monitoring the growth of insect larvae using a regression convolutional neural network and knowledge transfer

Paweł Majewski [a], Mariusz Mrzygłód [b], Piotr Lampa [b], Robert Burduk [a], Jacek Reiner [b]

Computers and Electronics in Agriculture
Volume 216, January 2024, 108503

Computer vision and deep learning in insects for food and feed production: A review

Sarah Nawoya [a b], Frank Ssemakula [b], Roseline Akol [b], Quentin Geissmann [a], Henrik Karstoft [c], Kim Bjerge [c], Cosmas Mwikirize [b], Andrew Katumba [b], Grum Gebreyesus [a]

SmartLarva

FLYgene

Laser Larvae

FLYBREED

Larval growth and sex

Proof of concept

Can image analysis be used for larval phenotyping?

- Small size
- Deformity
- Sexual monomorphism

Simplest scenario

- Individual larvae
- In-lab

Setup

Image acquisition
(n = 1500 larvae)

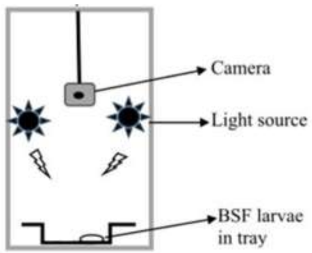
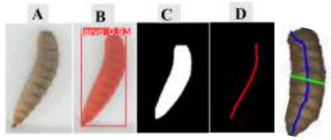


Image processing
(YOLOv8)

Detection and segmentation



Detection and Cropping

Manual data acquisition

Larval Weight, sex

Prediction

Feature-based prediction

Area, length

Area, length, width

Weight

Image regression

Weight

Classification

Sex

Male?

Female?

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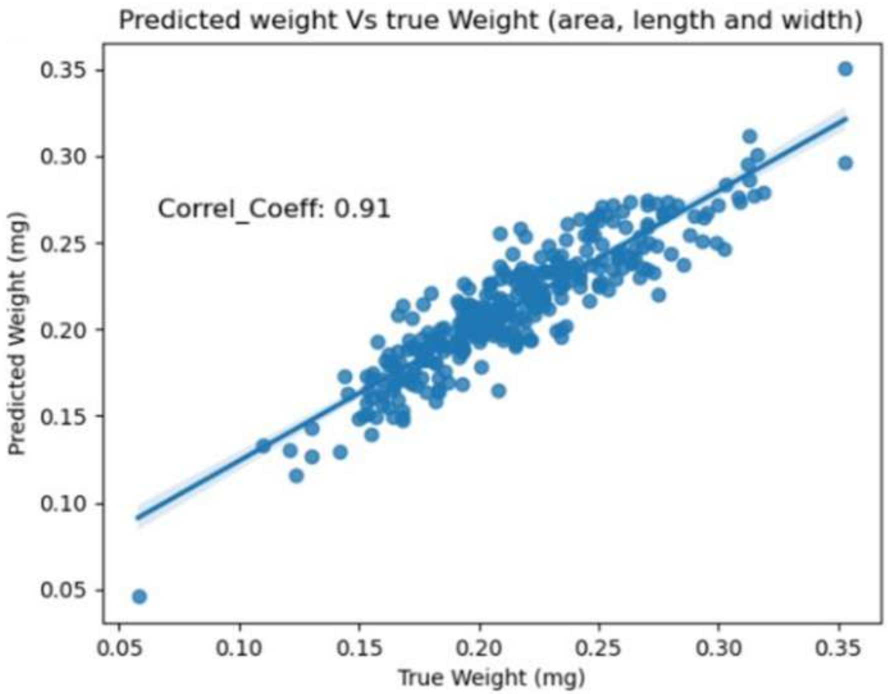
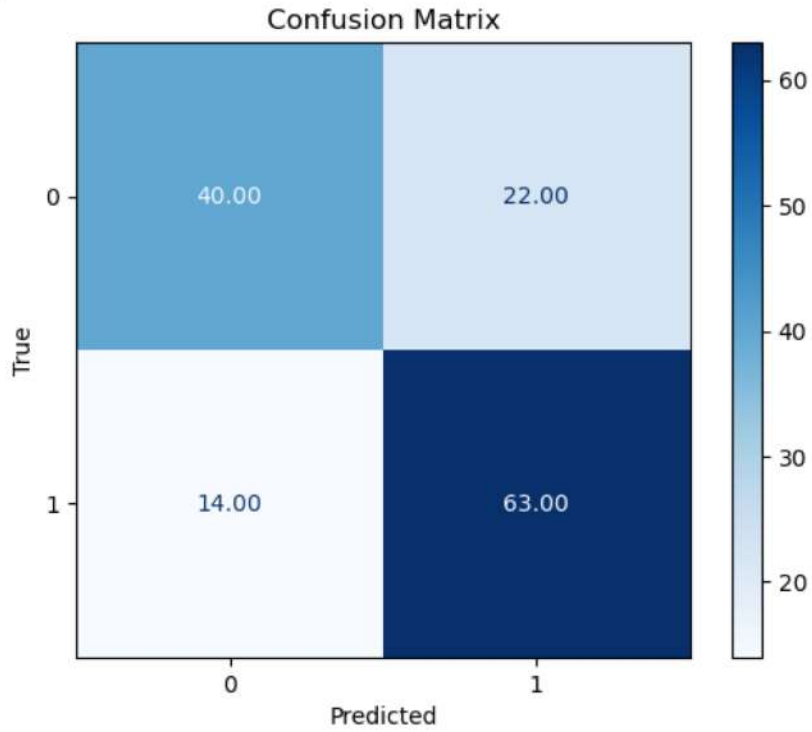
TECHNICAL SCIENCES

PREDICTION





Accuracy: 74%
F1 score: 0.75

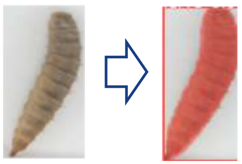
CONCEPT TO APPLICATION

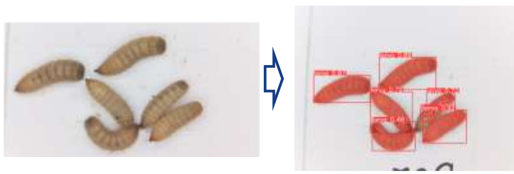
Individual larvae detection & prediction

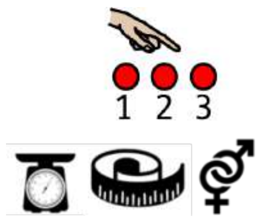
Individual larvae detection from group of larvae

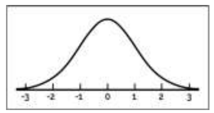
Family-crates
Denser group with substrate

Select family based on family-averages

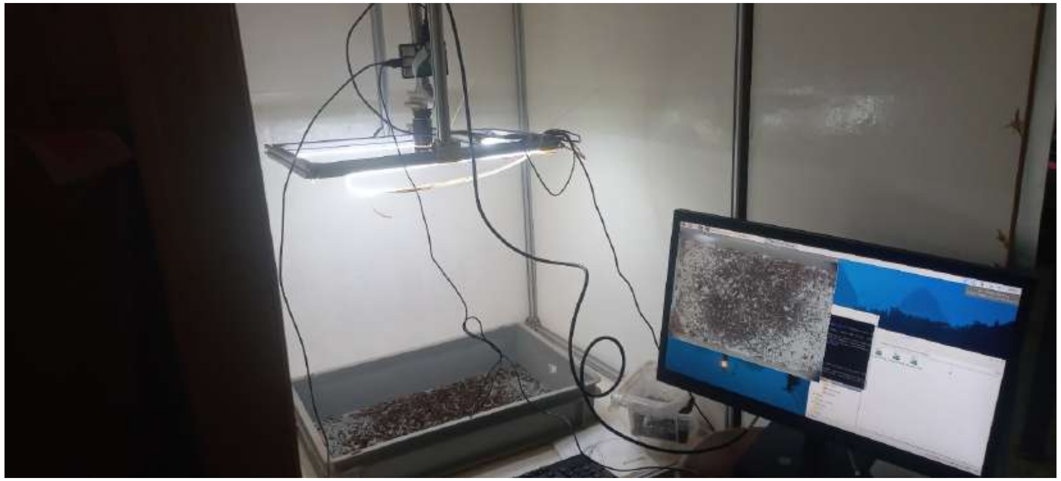


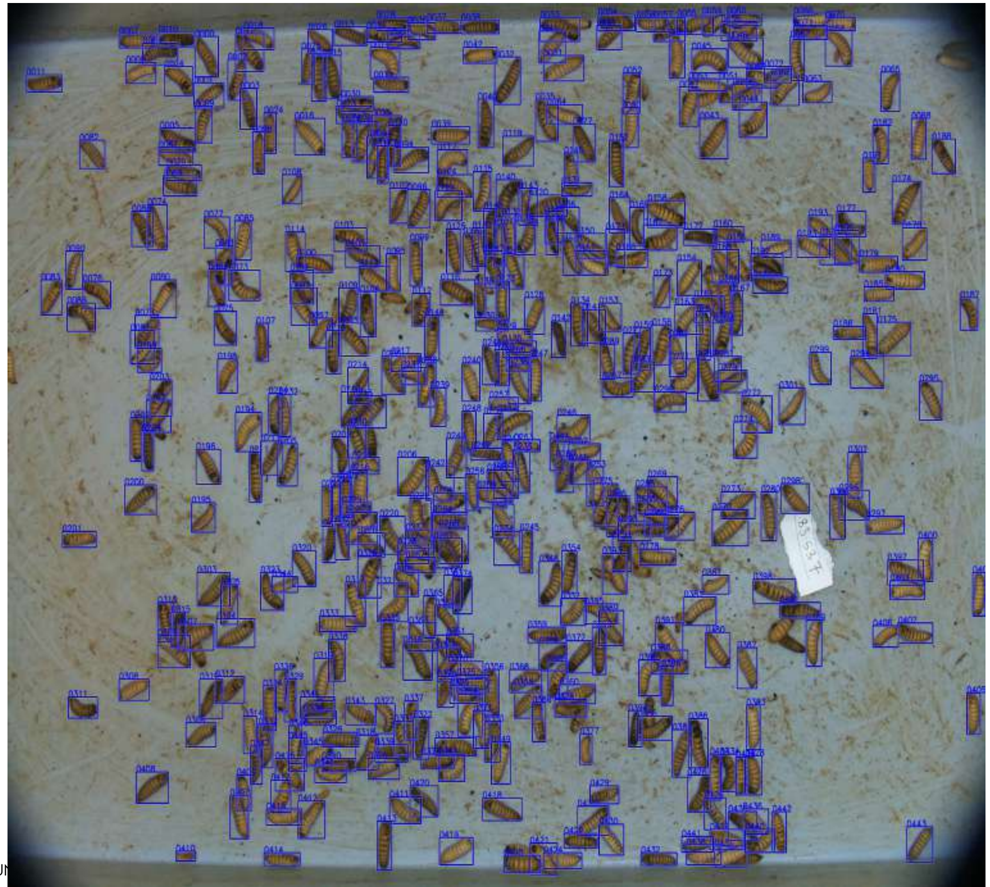




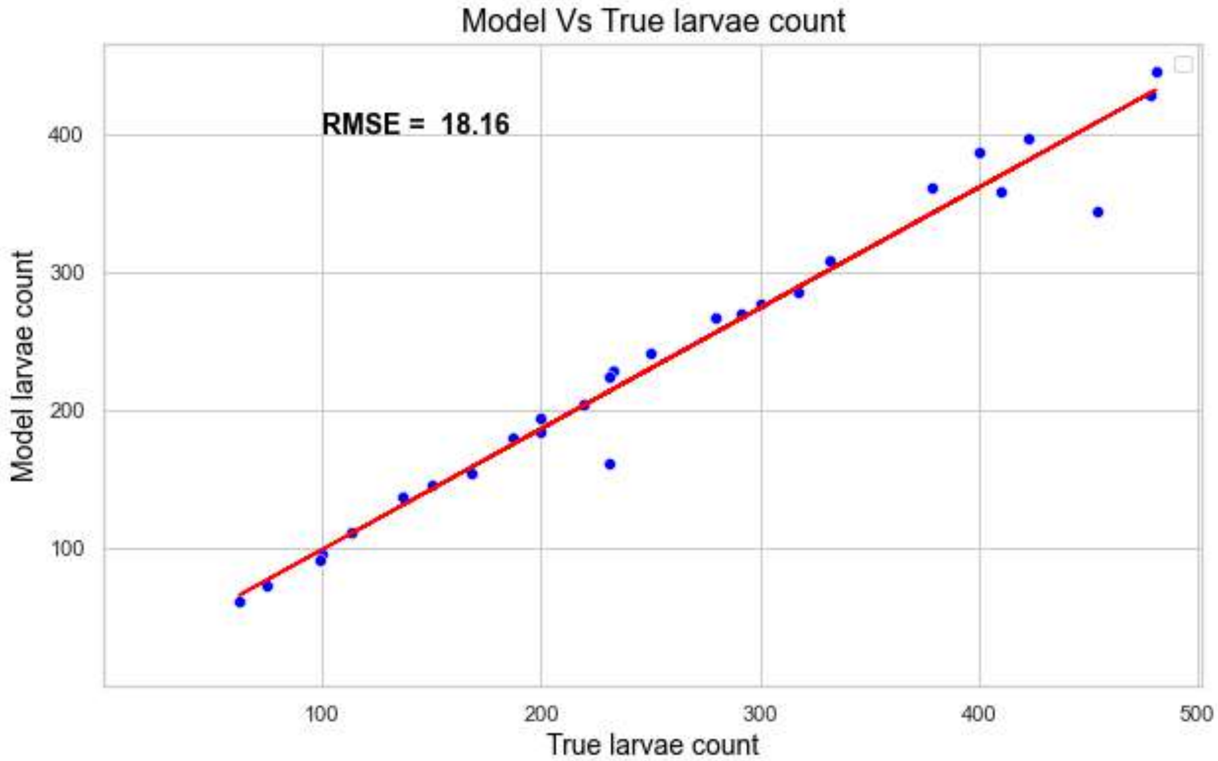


IN-CRATE IMAGING FOR LARVAL COUNTING AND WEIGHT PREDICTION

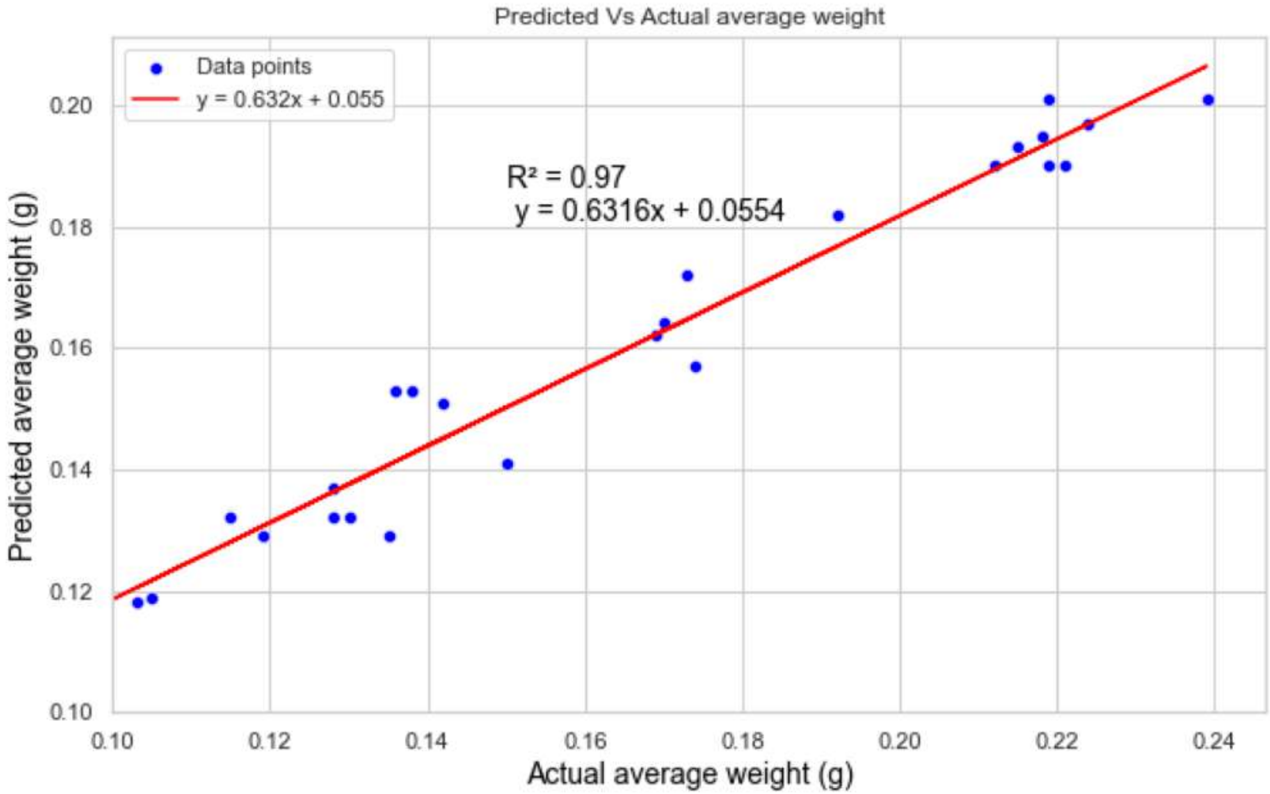




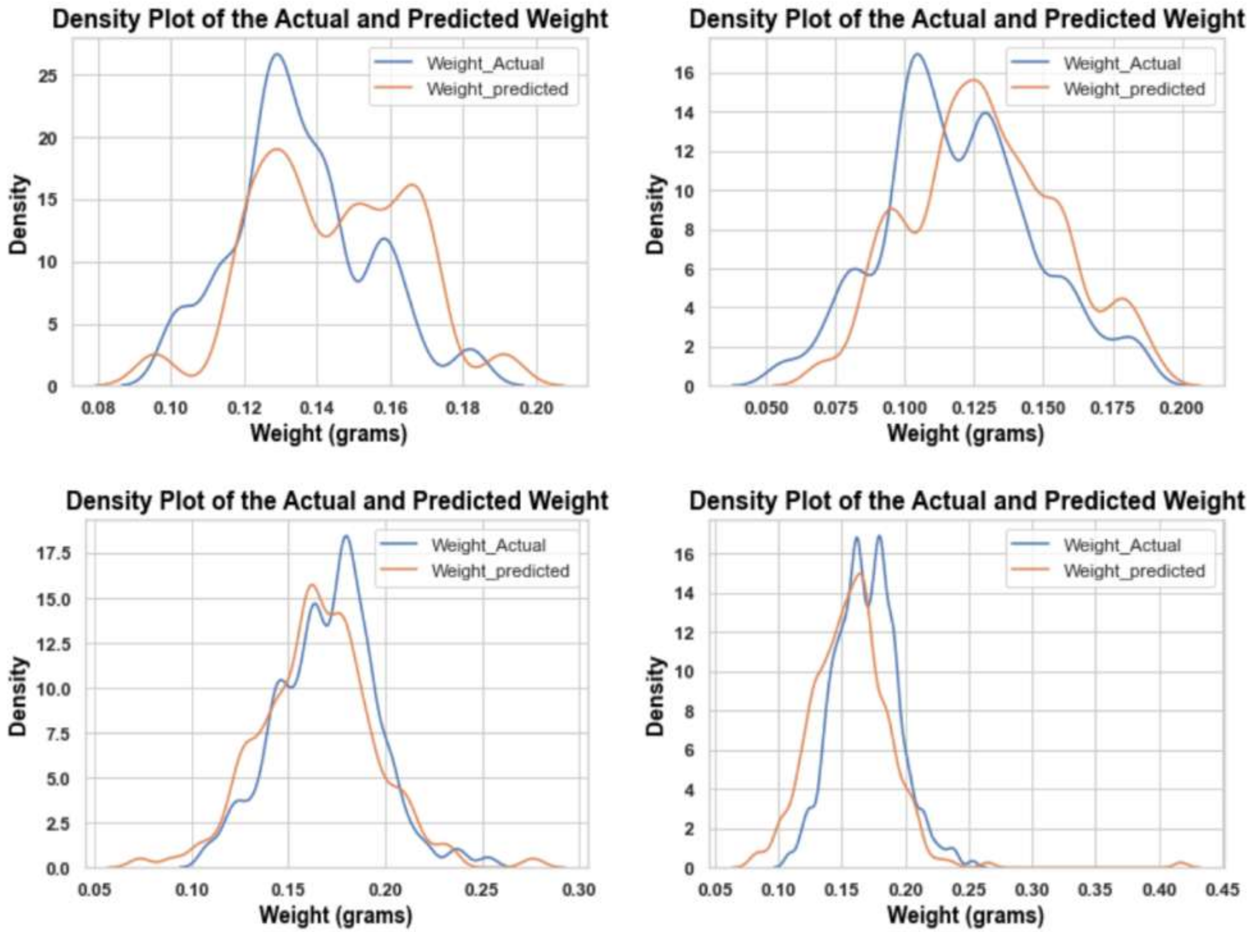
COUNTING ACCURACY



Group-level average weight prediction



Weight distribution within groups

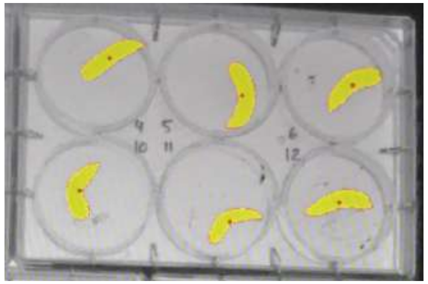


"Off-the-shelf" solutions

EthoVision XT

Pre-built, "complete" commercial solutions for specific tasks without extensive customization

- Typically, costly
- Low throughput
- *Raw data often "hidden" from users*
- *Internal algorithms and filtering*

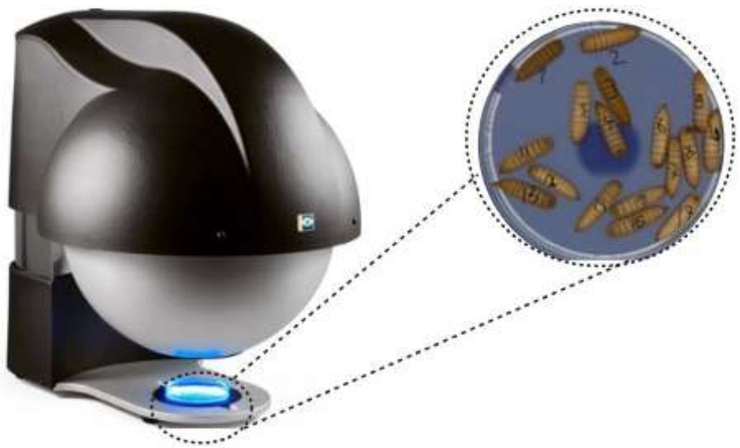


Spectroscopy and spectral imaging

Chemical composition based on light absorption, emission, or scattering across wavelengths.

Hyperspectral imaging

- Combines machine vision & IR spectroscopy
- Information on both spatial and spectral aspects

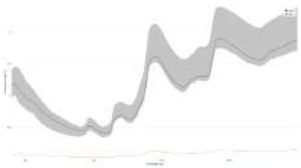


Larval nutritional contents

Larvae reared on various waste
Pig manure, maize bran, HH waste, etc
(Uganda, FlyGene)

Larvae reared on 17 diets
Different spikes of sugar and protein
(**Denmark, LaserLarvae**)

Hyperspectral imaging



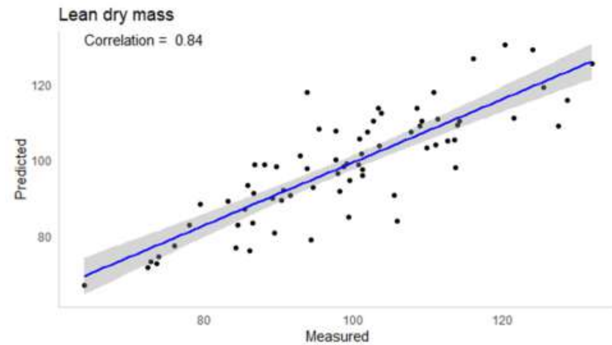
Extract spectral data

FOSS NIR Scanner D23

Total protein &
Fat

Chemical analysis

Fat, protein, fatty acid, amino acid.



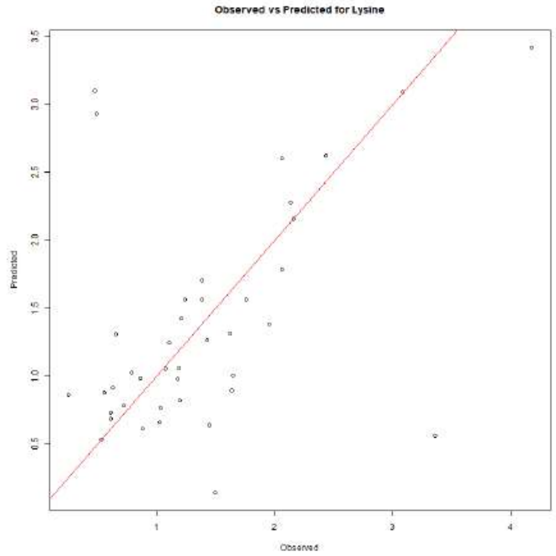
Model training & prediction

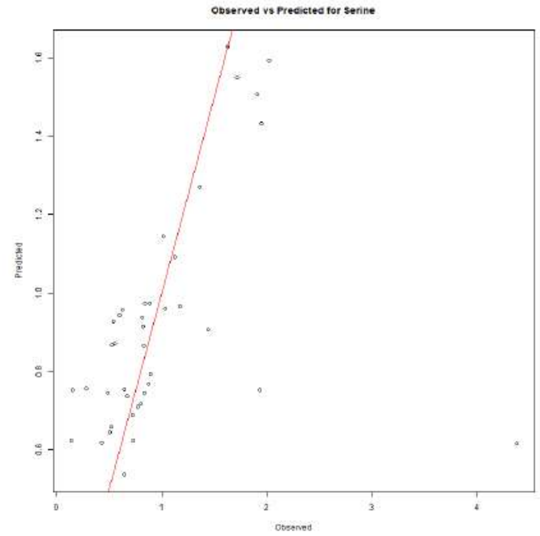
FLYgene

Laser Larvae

Prediction of detailed amino acid composition

Trait	Mean (mg/g)	Correlation	RMSE
Alanine	6.50	0.79	2.67
Arginine	1.09	0.80	0.59
Asparagine	0.06	0.80	0.05
Aspartate	0.33	0.37	0.25
Glutamate	2.41	0.89	0.74
Glutamine	5.89	0.64	4.65
Glycine	1.16	0.77	0.54
Histidine	2.32	0.92	1.03
Isoleucine	0.96	0.40	0.42
Leucine	1.25	0.45	0.68
Lysine	1.34	0.48	0.83
Methionine	0.20	0.59	0.13
Phenylalanine	0.64	0.52	0.23
Proline	5.61	0.75	2.83
Serine	0.95	0.38	0.68
Threonine	0.91	0.36	0.33
Tryptophane	0.63	0.65	0.19
Tyrosine	1.10	0.58	0.64
Valine	1.48	0.60	0.55





Beyond phenotyping?

Prospects for implementing CV based tracking and monitoring in production units?

Realtime continuous monitoring of growth

Larval activity

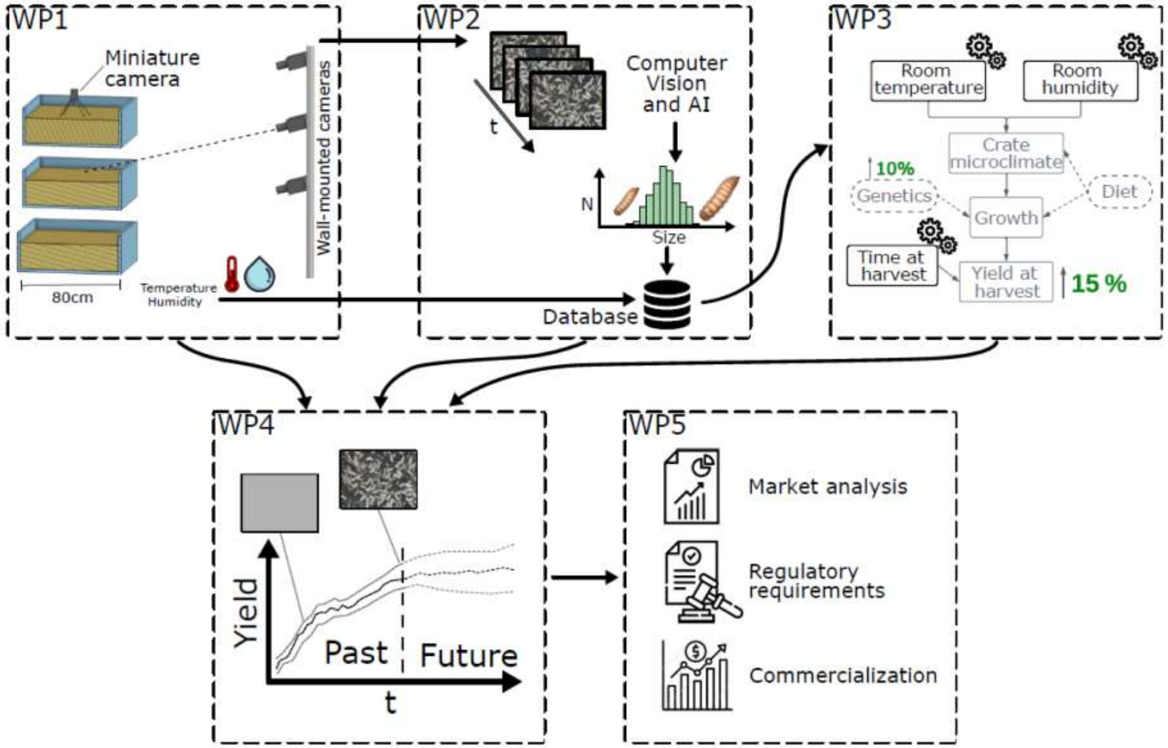
Substrate temperature

Escape

Optimizing harvest time

Feed utilization

Smartlarva: realtime monitoring for optimal harvest time decisions



Two TRL7 solutions:

(1) real-time distributed in-crate vision system for tracking larval growth and behavior

(2) phenotyping platform for automated larval sex classification and phenotyping

ENORM

BETTER INSECT SOLUTIONS

SKOV

Future prospects

Is digital phenotyping cure-all?

- Not all producers can afford (Cost)
- Technological obsolescence
- Individual ID-ing still a challenge
- Scaling/complete commercial solutions still drag

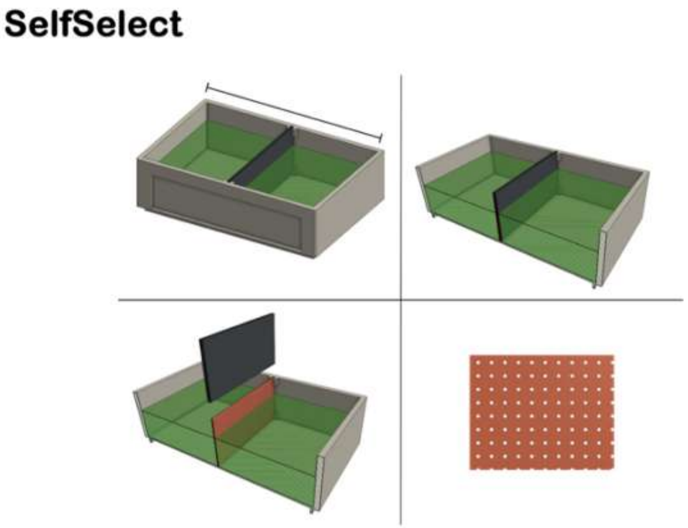
Future prospects

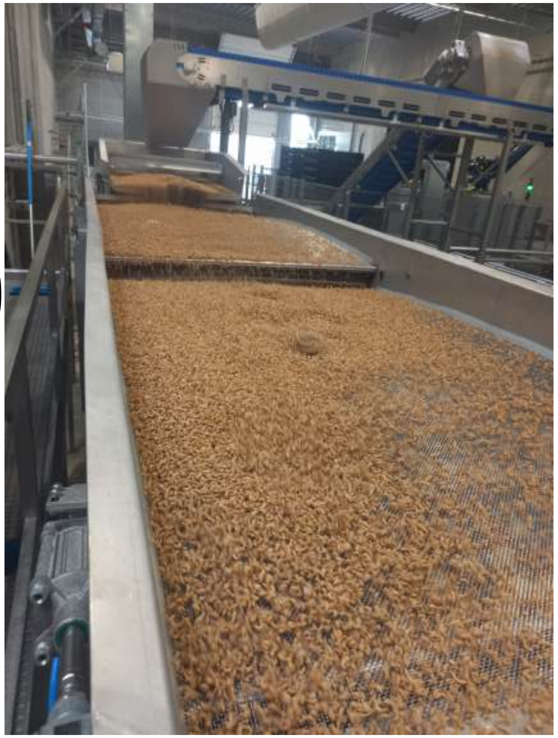
Industry shift- specialization

- Not all producers should be breeders!
- Dedicated for investment on breeding

Future prospects

"low tech" augmentations?
- Mechanical sorting?
- Sieving in mass selection for size (FlyGene project)





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MARULA PROTEEN LIMITED

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INSECT PRO

icipe

DANIDA

Danish International Development Agency

AUFF NOVA