Automated Recognition of Insect Meals for Animal Feed

using Optical Microscopy and Deep Learning

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Master's in Computer and Management Engineering
UMONS – CRA-W – Academic Year 2024–2025

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1. Project

Context

The use of insect-based meals in animal feed represents a major step toward a more sustainable agri-food sector. Insect such as *Tenebrio molitor* and *Hermetia illucens*, rich in protein and produced with a low environmental footprint, offer a credible alternative to traditional protein sources.

Current limitations in insect meal authentication through optical microscopy:

- Requires advanced entomological expertise
- High morphological variability depending on species, stage, or treatment
- Risk of confusion with other materials (e.g., krill, bone fragments)

A European proficiency test (RIKILT, 2017) revealed that **90%** of participating laboratories failed to detect insect material in samples enriched at 1%, as reported by Van Raamsdonk, van der Fels-Klerx, and de Jong in *New Feed Ingredients: The Insect Opportunity*.

Project Goal

To develop an automated recognition system capable of identifying insect-derived particles from optical microscopy images for use in official quality control procedures.

Implementation Strategy:

- **2 phases:** First, distinguish insect vs. non-insect; then, classify *Tenebrio* vs. *Hermetia* vs. non-insect
- Development of a dedicated microscopy image database
- Development of a deep learning model tailored to this task
- Final analysis and interpretation of classification performance

2. Implementation

Dataset

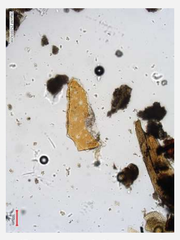


Figure 1 : Micrograph

Micrographs (Figure 1) were acquired using Keyence and Olympus microscopes from particles extracted via double sedimentation. Samples included ***T. molitor***, ***H. illucens***, and various non-insect materials (krill, fish bones, etc.). The particles, ranging from a few tens to several hundreds of micrometres, were manually annotated by an expert, with a focus on cuticle fragments for insect samples. The dataset contains **±6,500** annotated particles: *T. molitor* (±10%), *H. illucens* (±10%), others (±80%).

Extraction and preprocessing

Particles were automatically extracted from the micrographs using a YOLO-based object detection model (Figure 2). Prior to classification, each patch underwent preprocessing: resizing to a fixed dimension of 384×384 pixels, normalization using ImageNet mean and standard deviation values, and extensive data augmentation to enhance generalization. The augmentation pipeline included flipping, rotation, color jitter, Gaussian blur, as well as advanced techniques such as MixUp and CutMix.

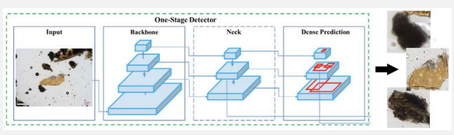


Figure 2 : YOLO extraction

Classification

Each extracted and preprocessed particle patch is processed by a classification model based on a convolutional neural network (CNN). The ConvNeXt architecture serves as the backbone and is extended with additional modules to enhance feature representation (Figure 3). The model outputs a confidence score for each class, reflecting the probability that a given input belongs to a particular category. For instance, as shown in Figure 3, when presented with a cuticle sample, the model predicted the 'insect' class with 95% confidence, assigning the remaining 5% to the alternative class.

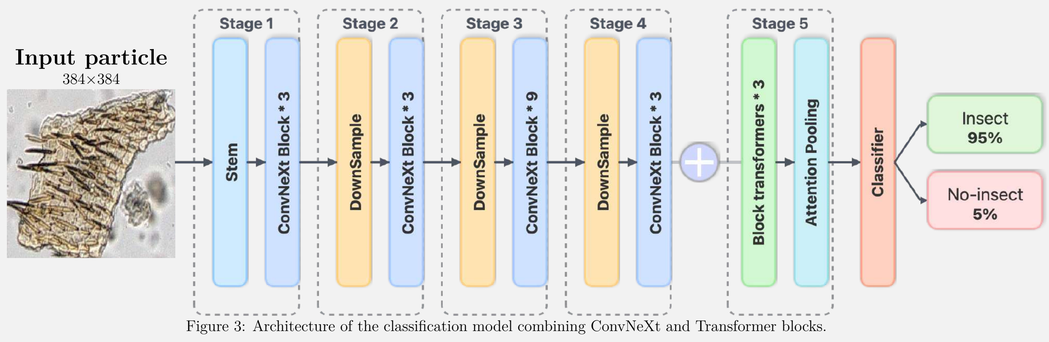


Figure 3: Architecture of the classification model combining ConvNeXt and Transformer blocks.

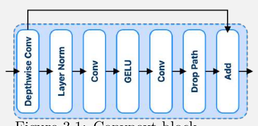


Figure 3.1: Convnext block

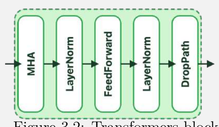


Figure 3.2: Transformers block

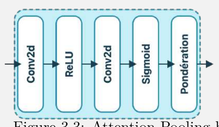


Figure 3.3: Attention Pooling block

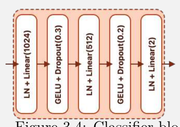


Figure 3.4: Classifier block

To enhance the extraction of non-local features, **Transformer blocks** were incorporated into the architecture. These self-attention mechanisms enable the model to capture global dependencies within a particle. For instance, in the case of a cuticle fragment, the model may identify consistent structural motifs or repeated patterns. Additionally, a **Attention Pooling** layer is employed to refine the feature map by emphasizing the most informative regions of each patch.

To leverage existing visual representations, transfer learning was employed by initializing the models with weights pre-trained on large-scale image datasets such as ImageNet. These models were then fine-tuned to adapt to the specific task of particle classification. Training was carried out using 80% of the available dataset, while the remaining 20% was reserved for validation. The **ConvNeXt** model, enhanced through task-specific modifications, achieved the highest performance. In addition, measures were taken to address class imbalance.

3. Results and Analysis

Validation, Confusion Matrices and t-SNE

Figures 4 and 5 present the confusion matrices for binary and three-class classification tasks, respectively. The model achieves high performance in both scenarios, with a Matthews Correlation Coefficient (MCC) of **0.92** in the binary case and **0.91** in the three-class setting. The MCC ranges from −1 (complete disagreement) to +1 (perfect prediction), and is particularly appropriate for evaluating classifiers on imbalanced datasets. Most misclassifications occur between *Tenebrio* and the Other class, which may be explained by their visual similarity and the inclusion of unidentified insect particles within the Other category. A 5-fold cross-validation was conducted, yielding an average MCC of approximately 90% across all folds.

Figure 6 displays a *t*-SNE (t-distributed Stochastic Neighbor Embedding) projection of the learned feature space. The embedding reveals well-separated clusters for the three classes, particularly for *Hermetia* and *Tenebrio*, confirming the model's ability to extract meaningful and discriminative representations.

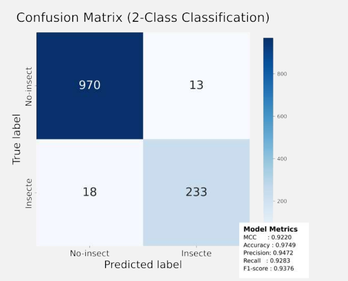


Figure 4: Confusion matrix – 2-class

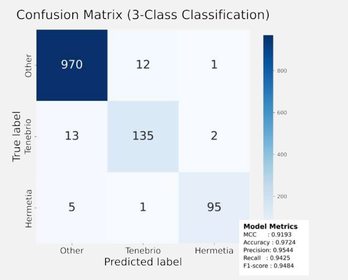


Figure 5: Confusion matrix – 3-class

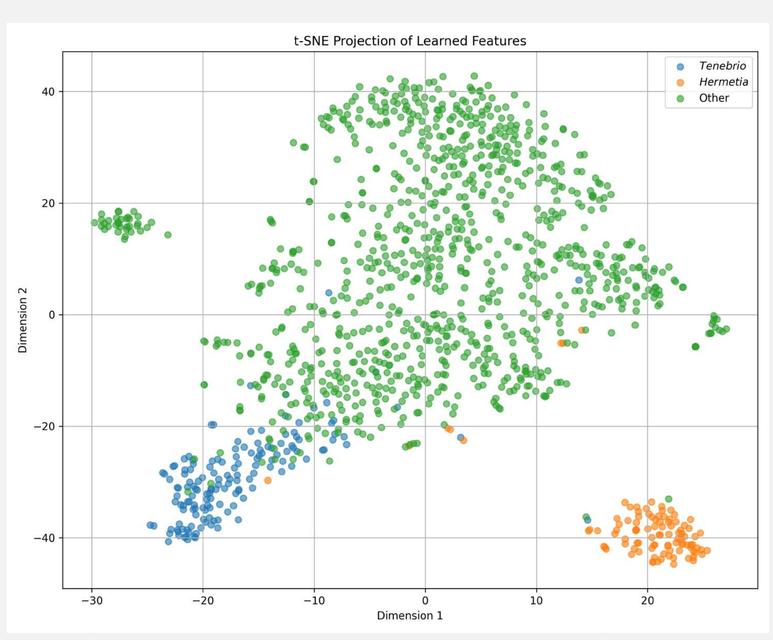


Figure 6: *t*-SNE projection of the feature vectors extracted by the model for all classes (*Tenebrio*, *Hermetia*, and Other). Each point represents a classified particle, and colors indicate the ground truth class. Well-separated clusters suggest that the model has learned discriminative representations for each category.

Tests

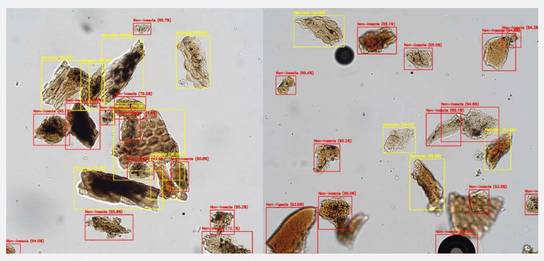
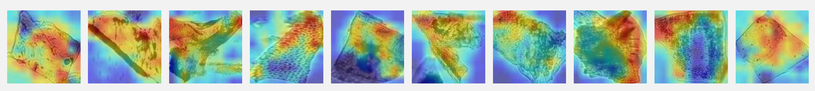


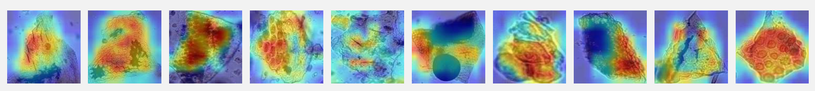
Figure 7: Tests, samples containing Hermetia

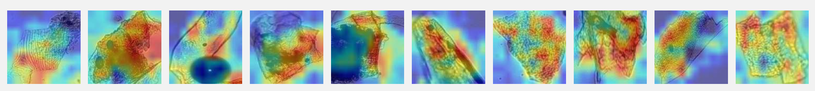
As a test example, Figure 7 shows a sample containing *Hermetia*, where the predicted classes and confidence scores are indicated by bounding boxes: red for non-insect, yellow for *Hermetia*, and green for *Tenebrio*. This approach can be integrated with a Keyence microscope using full-slide scanning mode to automate the detection and counting of particles across entire slides. Additionally, the model can be deployed on mobile devices to enable real-time inference through a smartphone camera, allowing for portable, on-site screening.

Grad-CAM

Grad-CAM highlights the image regions most relevant to the model's prediction. We observe that it focuses on contours and internal patterns. For example, in *H. illucens*, the model often attends to surface hairs and texture motifs, showing it uses meaningful visual cues for classification.

***T. molitor*:** 

***H. illucens*:** 

Other: 

Conclusion

This project demonstrates the feasibility of an automated recognition system for insect meals using optical microscopy and deep learning. Leveraging a dedicated image dataset and a ConvNeXt-based model enhanced with Transformer modules, the system achieves high and consistent performance, with a Matthews Correlation Coefficient of 0.91 in the three-class classification task. The solution can be integrated with microscope scanning systems or deployed on mobile devices, enabling fast and reliable on-site screening. This work marks a promising step toward more automated quality control in the agri-food sector.