# A 3D Laser Profiling System with Machine Learning for Online, Automated Grading of Poultry Meat with Woody Breast

**Jiaming Zhang, Xinyang Mu, Yuzhen Lu*** (luyuzhen@msu.edu)
Department of Biosystems and Agricultural Engineering, Michigan State University, East Lansing, MI 48824

Department of Biosystems and Agricultural Engineering
MICHIGAN STATE UNIVERSITY

## Introduction

- Woody breast (WB) myopathy in poultry remains an economically important issue for the poultry industry, characterized by abnormal hardness and pale areas in chicken breast fillets [2].
- Current detection methods rely on manual palpation and visual inspection, which are labor-intensive, inefficient, and subject to human subjectivity.
- WB-affected chicken fillets exhibit distinctive morphological features, including cranial bulging and caudal ridge-like formations, which can be captured through three-dimensional (3D) imaging techniques.
- In our prior research [1], structured light imaging showed promise for WB assessment but had limitations for online, real-time inspection. Typical depth or RGB-D (red-green-blue-depth) cameras lack the necessary accuracy for capturing surface details.
- This study aims to develop and evaluate a novel laser-based 3D profiling system with artificial intelligence for online, automated detection and grading of WB.

## Platform Development (Obj. #1)

- The 3D laser profiling system consists of dual line lasers (red and blue), a high-speed color camera, and a speed-adjustable conveyor belt (**Fig. 1**).

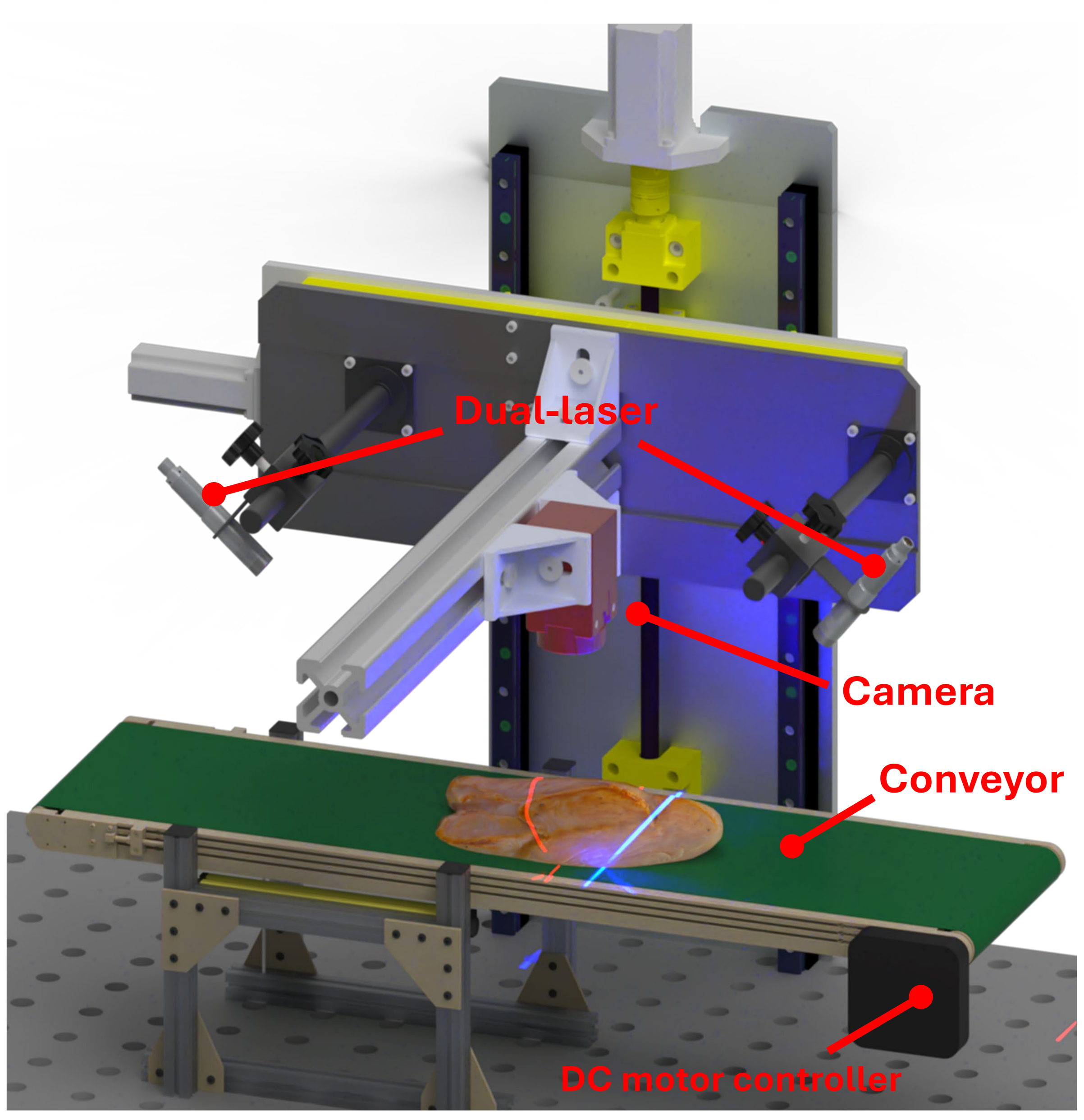


**Fig. 1 Schematic of the 3D laser profiling system with line lasers and camera for surface reconstruction.**

- A comprehensive geometric calibration protocol was developed to ensure accurate mapping between the camera and laser planes.
- An automated algorithm pipeline (**Fig. 2**) was developed for real-time image acquisition, processing, and 3D reconstruction @107.07 FPS (**Fig. 3**).
- The 3D reconstruction accuracy (**Tab. 1**) was evaluated using a standard trapezoidal calibration block (TCB) of knowledge dimension.

**Table 1 Reconstruction accuracy at different conveyor speeds.**

| SPEED (CM/S) | MEAN ABSOLUTE ERROR (MAE, MM) | | | MEAN PERCENTAGE ERROR (MPE, %) | | | DENSITY (PTS./$cm^2$) |
|---|---|---|---|---|---|---|---|
| | X | Y | Z | X | Y | Z | |
| 5 | 1.580 | 0.518 | 0.287 | 1.500 | 0.680 | 0.867 | 82.7 |
| 10 | 1.751 | 3.440 | 0.732 | 1.662 | 4.516 | 2.206 | 46.6 |
| 15 | 2.133 | 5.301 | 2.555 | 2.025 | 6.959 | 7.698 | 31.0 |
| **Avg.** | **1.821** | **3.086** | **1.192** | **1.729** | **4.051** | **3.590** | |

- The results shown in **Tab. 1** demonstrate MAE and MPE across all axes at different speeds.

## Materials

- A total of 310 chicken breast fillets, including 117 normal and 193 WB-affected samples, were collected from a commercial processing plant (Miller Poultry, Orland, IN), where the ground-truth WB of samples was performed by trained personnel.
- The chicken samples were imaged online by projecting dual-laser lines onto the sample surface as the sample was moving on the conveyor, which was performed at three different conveyor speeds of 5, 10, and 15 cm/s, respectively.

## Modeling for WB Classification (Obj. 2)

- Utilizing the ray-plane intersection principle, subpixel-detected laser line positions were transformed into 3D coordinates. Plane-fitting and clustering algorithms were applied to isolate the chicken from the total point cloud. Surface features were subsequently extracted from the reconstructed 3D model (**Fig. 2**).
- **Baseline Method [1]**: Each 3D point cloud was first projected from the top-down view to obtain a 2D depth map. Then conventional feature extractors were applied, including Local Binary Patterns (LBP) to capture the local texture and Binarized Statistical Image Features (BSIF) to encode global texture. The LBP and BSIF histograms were concatenated into a unified feature vector, which was fed into a binary support vector machine (SVM) classifier, representing baseline performance in sample classification.
- **Deep Learning (DL) Method:** An enhanced PointNet [3] architecture incorporates multi-scale feature extraction and attention mechanisms to directly learn the 3D features of the point cloud. This approach is designed as an end-to-end network that simultaneously learns features and performs classification without a separate feature extraction step.

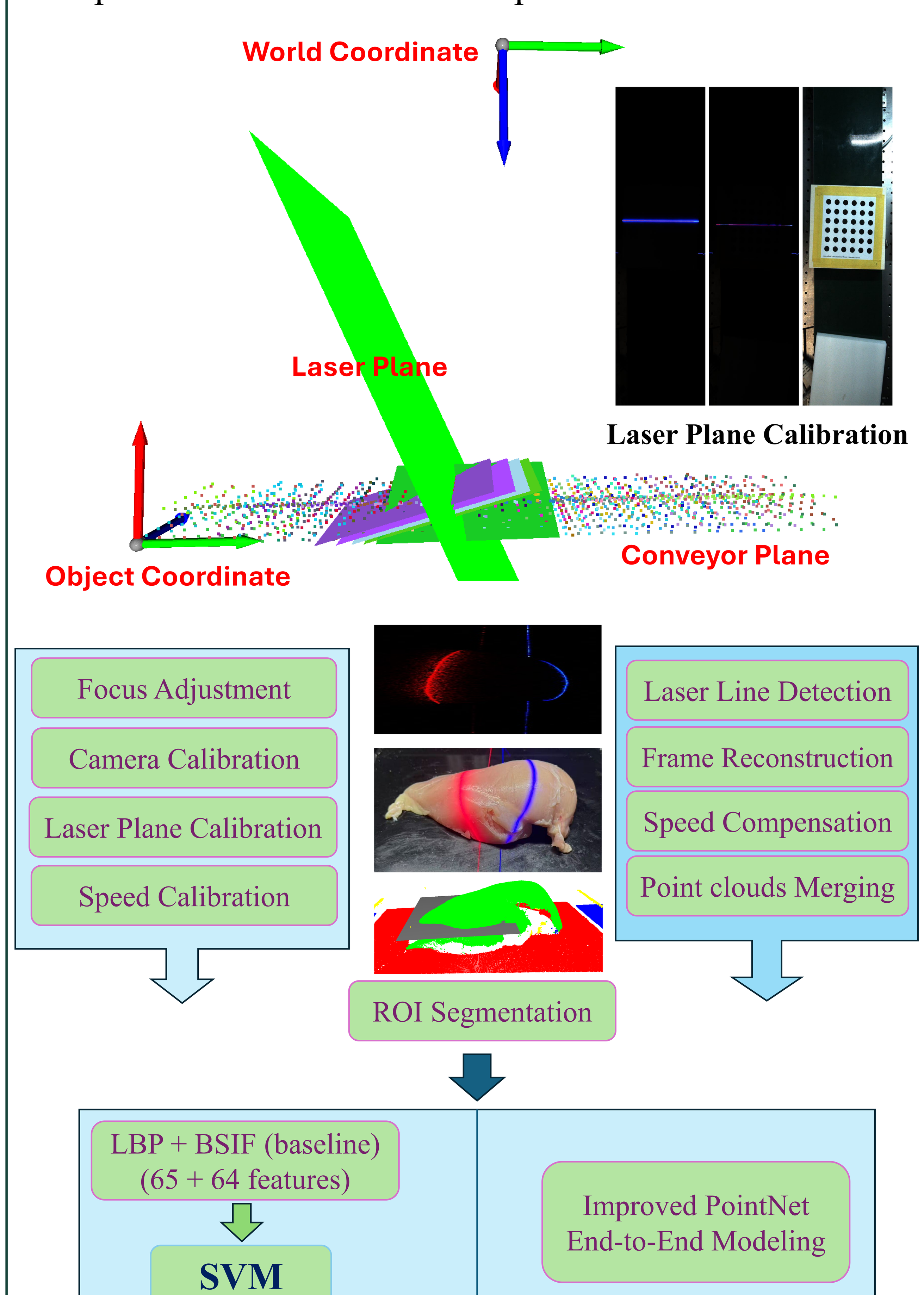


**Fig. 2 Automated Pipeline for Reconstruction and Classification.**

- Model classification performance was evaluated using repeated validations [1], with 50 replications.

## Results

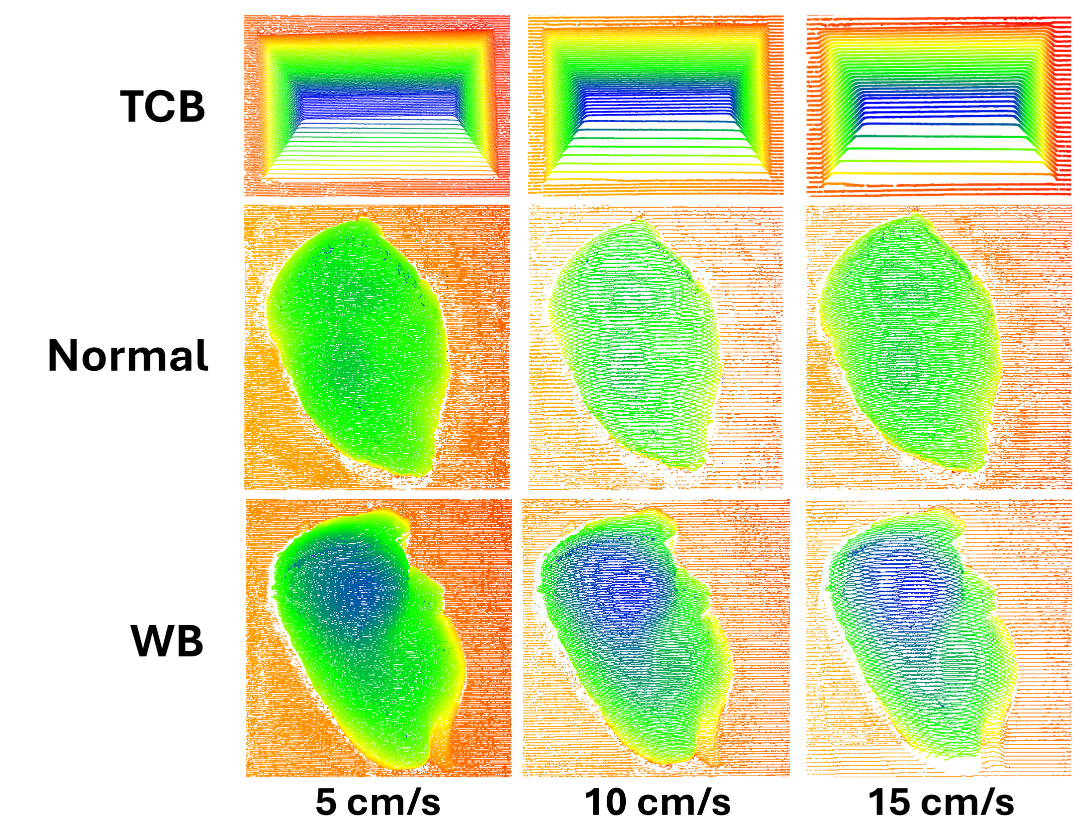


**Fig. 3 Reconstruction Results at Different Scanning Speeds. (TCB: Trapezoidal Calibration Block)**

- In classification evaluations (**Table 2**), the system achieved overall classification accuracies of 87.78%, 87.08%, and 86.79% at three conveyors, respectively.
- The increase in Y-axis error was mainly caused by instability in conveyor motor speed (**Fig. 4**) and variations due to object weight.

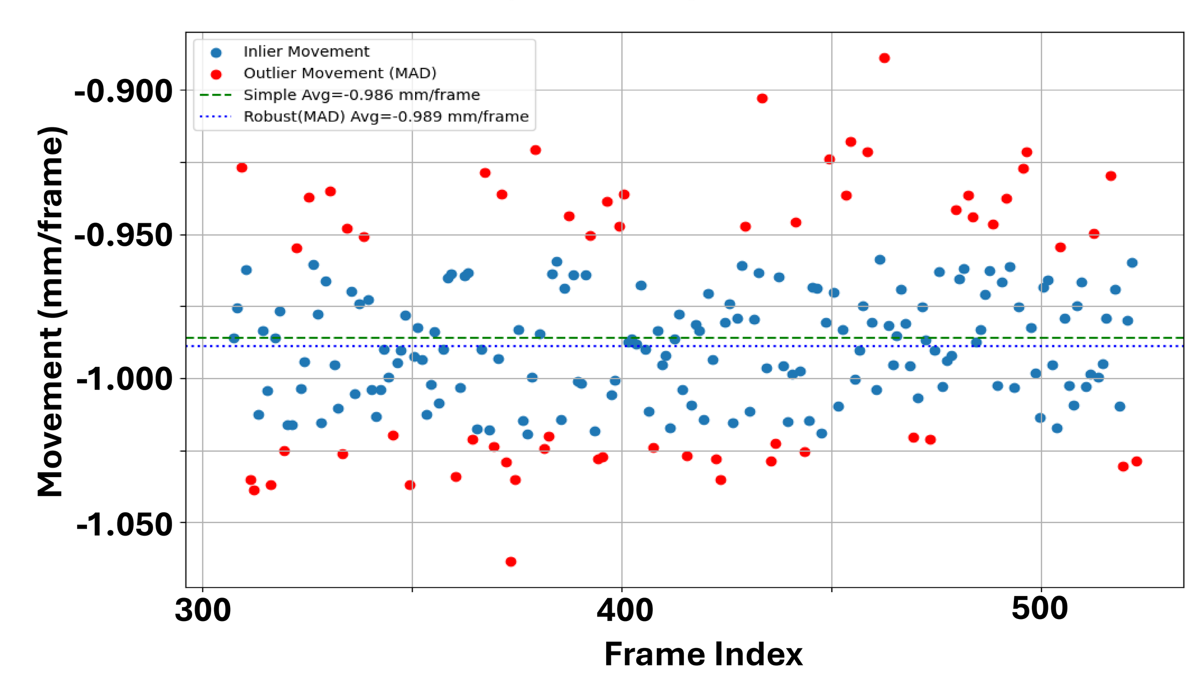


**Fig. 4 Speed calibration results at 10 cm/s.**

**Table 2 Classification Results.**

| Method | LBP + BSIF (baseline) | Deep Learning (DL) | |
|---|---|---|---|
| | Test Acc. | Train Acc. | Test Acc. |
| **5 (cm/s)** | 85.17% | 0.9231 | 0.8778 |
| **10 (cm/s)** | 84.69% | 0.9203 | 0.8708 |
| **15 (cm/s)** | 85.01% | 0.9375 | 0.8679 |

- The proposed algorithm pipeline achieved real-time processing, averaging **9.34** milliseconds per frame on a computer (11th Gen Intel i9-11900K processor, 128 GB RAM).

## Conclusion

- A novel 3D laser profiling system was built and validated for online, automated assessment of poultry meat with WB condition.
- The proposed 3D algorithm pipeline coupled with DL consistently outperformed that with the baseline method, with accuracy improvements of up to 2.61%, and the system appeared to have robust performance at varied speeds.
- Future research will improve the density, accuracy, and robustness of 3D reconstruction by the laser profiling system as well as deep learning network architectures towards practical application.

## Acknowledgment

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## References

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