Project Description

Nesteye • Real-Time Poultry Monitoring & Piling Intervention System

Project Objective

Develop a multi-modal computer vision system capable of:

- Real-time detection of dangerous bird piling and clustering from overhead barn camera footage.
- Continuous, full-flock weight estimation without manual handling or sampling.
- Early detection of disease and mortality risk from behavioral and visual cues.
- Autonomous intervention (adaptive LED and sound dispersal) to break up piling events before birds are lost.

Model Architecture Overview

Component	Details
Piling Detection	Custom CNN, YOLO-based instance segmentation, fine-tuned to identify bird clusters, density, and pile formation in real time.
Weight Estimation	Segmentation-derived body area and keypoint features fed into a regression head (EfficientNet backbone) to estimate individual and flock-average weight from overhead RGB/IR frames.
Disease / Mortality Detection	ConvNeXt-based classifier trained on movement, posture, and thermal signatures to flag early behavioral anomalies associated with illness or mortality risk.
Real-Time Inference	Optimized with NVIDIA TensorRT and deployed on Jetson Orin Nano for on-barn, edge-based processing with no cloud dependency.

Data Sources

Public and Academic Datasets

- Research aviary data from the University of Georgia and Texas A&M poultry science programs.
- Published poultry behavior and weight datasets from peer-reviewed papers.
- Supplementary broiler datasets from Pakistani commercial flocks, used to increase breed and environment diversity.

Proprietary Data

- Live footage from Nesteye's 5 active commercial barn pilots (Texas and Washington), used to validate and harden models under real-world dust, lighting, and density conditions.

Synthetic Data (via NVIDIA Omniverse)

- Procedurally generated barn scenes with varying camera height, angle, lighting, and bird density.
- Used specifically to make the piling and weight models robust to inconsistent camera mounting heights across different barn types, a major source of real-world variance that is expensive to capture with live footage alone.

NVIDIA Software Stack Integration

1 · NVIDIA Omniverse (Synthetic Data Generation & Simulation)

- Used to simulate realistic barn environments with varying camera placement, lighting, litter conditions, and flock density.
- Procedural generation of piling and non-piling scenarios to expand training data beyond what live pilots can capture.
- Auto-labeling for bird bounding boxes, segmentation masks, and cluster density classes.

2 · NVIDIA Isaac Sim

- Extends Omniverse simulation with physics-based bird movement and clustering behavior for more realistic synthetic training scenarios.

3 · NVIDIA TAO Toolkit

- Used for transfer learning and fine-tuning pretrained vision models on poultry-specific data, accelerating model iteration between pilot sites.

4 · NVIDIA DeepStream

- Real-time video ingestion and inference pipeline for barn camera feeds, running on the Jetson Orin Nano at each barn.

5 · NVIDIA TensorRT

- Final optimization layer for piling detection, weight regression, and disease classification models.
- Supports INT8/FP16 precision to hit real-time inference targets (<30ms/frame) on Jetson Orin Nano hardware.

6 · Jetson Orin Nano (Edge Deployment)

- On-site edge compute for all inference, keeping the system functional without reliable barn internet and enabling autonomous piling intervention with no cloud round-trip latency.

Execution Timeline

Phase	Duration	Tasks
Setup	Weeks 1–2	Set up Omniverse and Isaac Sim environments; establish data pipeline from pilot barns and academic datasets.
Synthetic Data Generation	Weeks 3–5	Generate synthetic barn scenes with varied camera height, angle, and density; auto-label piling and weight training data.
Model Fine-Tuning	Weeks 5–9	Fine-tune piling detection, weight estimation, and disease classification models using synthetic, academic, and live pilot data.
Optimization	Weeks 9–11	Convert models to TensorRT; deploy to Jetson Orin Nano; test latency and throughput under real barn conditions.
Field Validation	Weeks 11–13	Validate against live pilot barns in Texas and Washington; compare model weight estimates against manual scale checks.
Finalization	Weeks 13–14	Refine intervention logic (LED/sound dispersal triggers); package model with documentation and demo.

Expected Deliverables

- A trained, working model capable of accurately estimating flock weight continuously and without manual sampling.
- Real-time piling detection and autonomous intervention pipeline (camera input to detection to dispersal trigger).
- Disease and mortality risk detection module trained on behavioral and thermal signals.
- Synthetic dataset from Omniverse covering varied camera heights, angles, and barn conditions.
- Evaluation report benchmarking accuracy, latency, and weight estimation precision against manual barn checks.
- Deployment package for Jetson Orin Nano, ready for install across additional pilot and commercial barns.

Future Opportunities

- Extend disease detection into predictive health scoring using longitudinal behavioral data across a bird's full growth cycle.
- Expand synthetic data generation to simulate additional species (layers, turkeys) as the platform generalizes beyond broilers.
- Integrate compliance reporting directly into the inference pipeline for automated welfare audit trails.

– Explore multi-barn fleet learning, where models improve across the full integrator network rather than barn by barn.