Danish entry 3.0: AI enabled biosecurity system for enhanced protection

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Abstract

This research presents a proof-of-concept for an intelligent biosecurity system specifically designed for use in livestock and poultry production settings. The system, known as the Danish Entry, employs a combination of multiple sensors and an image recognition system to enhance biosecurity measures on the farm. The camera integrated into the system is connected to a computer that runs a visual recognition model capable of identifying potential breaches in biosecurity protocols. The proposed design aims to reduce the likelihood of farm personnel misusing biosecurity procedures and transporting pathogens into the farm. Furthermore, it facilitates slower human traffic flow through the physical barriers within a Danish Entry, thus increasing visual detection accuracy. This system presents a promising solution for improving biosecurity in the livestock and poultry industry using technology and automated approaches.

Keywords: disease, swine, disinfection, pathogen, machine vision

Introduction

Biosecurity in livestock and poultry production systems is a critical aspect that ensures the production of safe, efficient, and affordable protein. Proper biosecurity involves using systems, equipment, and procedures to reduce the risk of introducing and spreading pathogens among animals. With the increasing number of devastating disease outbreaks in recent years, such as the Highly Pathogenic Avian Influenza outbreak in the U.S. and the African Swine Fever outbreak in China and Europe, the importance of proper biosecurity measures has become even more evident (Khanna, 2022). One of the common systems used to reduce the risk of introducing pathogens inside livestock farms is the Danish Entry System, which consists of a bench that creates a line of separation between two zones at the facility's entrance. However, this approach relies on the trust of personnel to adhere to the proper procedures, and the manual review of biosecurity procedures at a Danish Entry can be costly and time-consuming. The Danish Entry 3.0 project provides a technological integration with a conventional Danish Entry by equipping the bench with sensors and a remote visual inspection system, which runs an object detection system capable of identifying and predicting biosecurity breaches in a swine production setting and providing an inexpensive and automated assessment of the biosecurity procedures.

Problem statement

There is a lack of technology-integrated, automated approaches for on-farm biosecurity programs. The strict upholding of a biosecurity program is crucial to reduce the risk of pathogen exposure to a healthy herd and preventing and minimizing endemic disease transmission. Current swine production facilities require their staff and visitors to follow certain biosecurity protocols, such as showering in and out of the facility, changing/cleaning boots, and restricting/cleaning supplies coming into the farm. To ensure that these protocols are being followed, human supervision is required, which can be flawed, subjective, and expensive since farms pay third-party services to manually review recorded or live stream videos to detect biosecurity transgressions.

The criteria of this project are to create an intelligent physical barrier to keep pathogens from entering animal production facilities by performing real-time visual detection and evaluation of biosecurity procedures.

Moreover, the system must be easily upgradable – since new biosecurity concerns might arise in the future. In terms of constraints, there are: the computer processing power, amount and quality of data available for training, image quality during real-time detection (such as low frames per second and poor lighting), the timespan in which detection can occur, and lastly, possible image noise (such as a non-solid color background wall).

Design goals

This project aims to upgrade the standard concept of a Danish Entry System (Figure 1) by installing a combination of sensors and cameras trained with an object detection system capable of identifying and predicting biosecurity transgressions in a swine production setting. It is proposed the use of an intelligent Danish Entry System that slows down farm personnel to allow enough detection time for an object detection model, which is capable of distinguishing dirty and clean boots and the use of personal protective equipment (PPE) such as masks, gloves, earplugs, and coveralls.

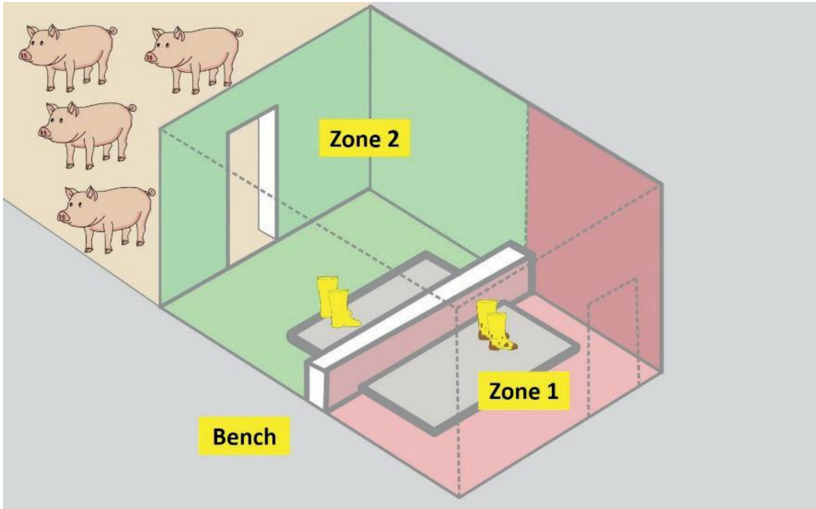

Figure 1: Danish Entry System depicting three areas of interest in which human actions and presence need to me detected: Zone 1, the Bench, and Zone 2.

Materials and methods

Danish entry system

The system utilizes two tandem sensors, a force-sensing resistive sensor, and an infrared proximity sensor, to achieve high detection accuracy. The signals from each sensor are interfaced and conditioned by a microcontroller (Arduino UNO). The system is designed to detect human actions and presence in three areas of interest: Zone 1, the Bench, and Zone 2 (Figure 1).

Zone 1 and 2 are the areas where a typical human behavior would be standing in front of the bench before sitting down and changing boots. Therefore, the best way to sense the presence of a person in those areas is by using a floor pressure mat (A and B in Figure 2). Assuming that a person is going from Zone 1 into Zone 2, the mat installed in Zone 1 will detect the presence of a person when they are about to sit down and change boots. Similarly, the mat installed in Zone 2 will detect the presence of a person when they finish changing boots and are about to leave the area.

In the Bench Zone, there are two sensing scenarios that need to be monitored. The first scenario is when a person is seated on the bench; for that reason, the bench is equipped with a force pressure sensor (C in Figure 2). The second scenario is when the line of separation is breached by someone crossing the bench without changing boots; thus, an infrared proximity sensor (D in Figure 2) was installed above the bench covering the line of separation.

Figure 2: (Left) Shows the installation of FSRs sensors underneath the mat. (Right) Depicts the top view of the Danish Entry 3.0 System.

The system has the advantage of being able to be installed in any existing Danish Entry currently used in livestock facilities. The system comprises two standard light bulbs (150 W, 120 VAC) with sockets, two Class 6 Solid State Relays, one Arduino UNO board, one adjustable Infrared Proximity Sensor Module, and five long Force Sensitive Resistors (FSR). The FSR was chosen for its long length (61 centimeters) and operational range (100 g to 10 kg), which allows for detection to be separated into three scales (No detection, Medium Detection, and High Detection). The Infrared Proximity Sensor Module was chosen for its simplicity of operation and calibration and its detection range of 3 to 80 cm, which is ideal for this application. The Arduino UNO microprocessor was chosen for its sufficient analog and digital ports for the prototype stage of this project.

The final design includes the installation of the FSR on the bench surface and underneath the mats and the AC and DC components wiring. By combining the information collected by each sensor with a set of processing decisions, the Arduino microcontroller generates an output to the Solid-State Relays to turn on and off the warning lights and trigger the visual inspection system as needed.

Image annotation

A collection of images was gathered and labeled to create a training dataset for an object detection algorithm used to verify biosecurity practices and PPE usage. This study's key objects of interest were boots, face masks, and gloves. In order to train the machine learning algorithm, a considerable number of images were needed. To reduce the time spent collecting images, Kaggle was utilized as a convenient source of images. The dataset used in this study included 853 pictures of people with and without masks. However, publicly available image datasets, including boots and gloves typically used in swine production, were either non-existent or lacked high resolution; as a result, two additional datasets were created to specifically address this need (see Table 1 for information about the datasets).

Table 1: Summary of dataset information.

Object	Number of Pictures Used	Source
Boots	60 Clean Pairs; 116 Dirty Pairs	Created by Authors
Gloves	119 With Gloves; 126 Without Gloves	Created by Authors
Masks	100 With Masks; 100 Without Masks	Kaggle Datasets

Labeling images can be an intricate and time-consuming process; however, a large number of diverse, annotated images were needed to train the machine learning algorithms and increase the object detection precision. The labeling was performed using the software LabelImg, in which an object area of interest (AOI) was selected with the cursor and assigned its respective label/annotation. Each object had a different area of interest (see Table 2 for each AOI criterion).

Table 2: Criterion used to select area of interest.

Object of Interest	Criterion for Selecting Area of Interest
Boots	All the edges of the sole surface
Gloves	Tip of the fingers to beginning of the wrist
Masks	Middle of the nose to the end of the chin

Network selection

Network Architecture is the component of the overall pipeline responsible for defining the deep learning model structure. Multiple architectures are available, but each architecture has a different accuracy, prediction styles, input and output, and data flow through the convolutional layers. This application requires live object detection, which requires good accuracy and fast to moderate detection and processing rates. YOLO (You Only Look Once), Faster - RCNN, and SSD MobileNet (Single Shot Detector) are the three most popular architectures.

Three key considerations must be reconciled in selecting an algorithm: the object of interest size, the speed of detection, and the desired accuracy. Figure 3 (Sachan and Sinhal, 2018) shows the relationship between accuracy and speed. In addition, the relationship between accuracy and object size in Figure 4 (Sachan and Sinhal, 2018).

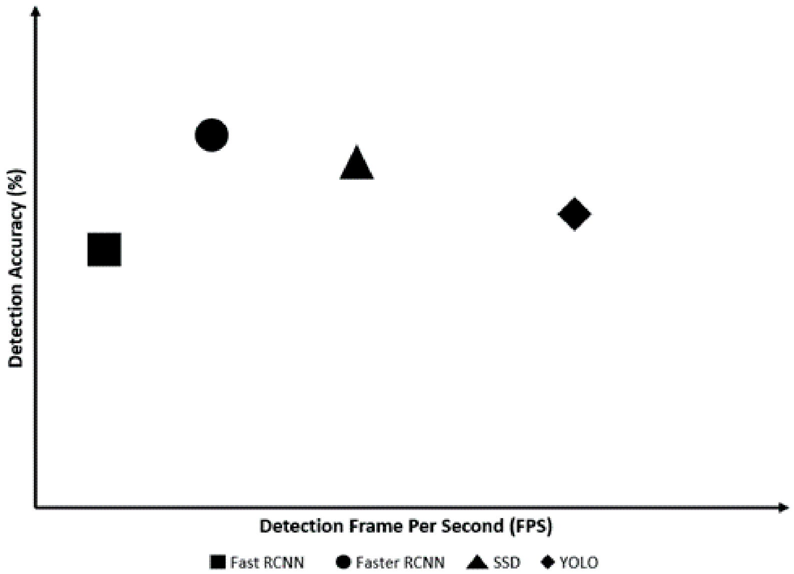

Figure 3: Accuracy versus speed relationship of the different network architectures.

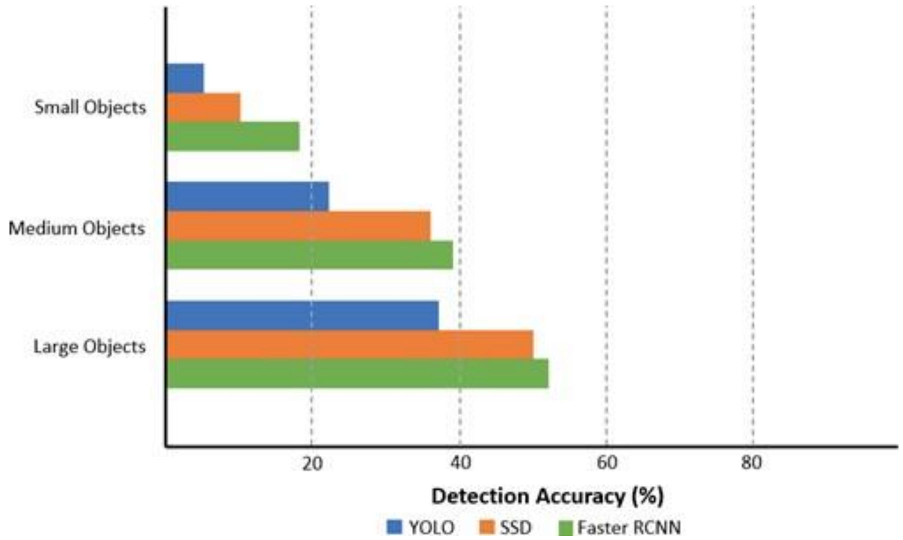

Figure 4: Accuracy versus object size relationship of the different network architectures.

The SSD MobileNet network architecture was implemented because it performs reasonably well in numerous categories (Renotte, 2021). This architecture performs well on medium-sized objects, and the detection speed is adequate since live video must be processed in near real-time, as people will be transiting and stopping for only about 10 seconds. Also, SSD MobileNet is considered well-suited because the accuracy/speed trade-off is minor on live video.

After selecting the SSD Mobilenet as the network, pre-trained models were selected from the TensorFlow 2 Detection Model Zoo, where the detection speed and mean average precision of several pre-trained models can be compared and selected.

Due to the proof-of-concept nature of this project, a pre-trained model that can detect objects fairly accurately and fast is needed; hence, the initial selection was the SSD MobileNet v2 FPNLite 320x320 (referred to as 320x320) because it was the SSD with the fastest detection speed and it would not require much computational processing power to perform the training and also, execute the model. However, a decision was made later on to try the SSD MobileNet v2 FPNLite 640x640 (referred to as 640x640) to observe if it would be, more accurate than the 320x320.

The 640x640 needed substantial computational processing power and time for model training. About six hours were needed to train the gloves detection model with 5,000 steps and about 13 hours were needed to train the boots detection model with 12,000 steps. In comparison, the 320x320 needed an average of four hours to train gloves, masks, and boots detection models.

Results and discussion

The Danish Entry System upgrades incorporated the integration of sensors, which performed as expected. The final prototype of the system was visually clean and structurally sound. After extensive testing and refinement of the logic, the working model was able to identify three distinct forms of human interaction with the physical barrier system. The first scenario involves the detection of an individual crossing the bench without changing their footwear. In this instance, the system activates warning lights on both sides of the separation zones, alerts the individual that proper biosecurity procedures have not been followed, and captures an image of the offender, which is timestamped and saved or can be automatically sent to the appropriate personnel.

The second scenario is when proper biosecurity procedures are followed. For example, when an individual moves from Zone 1 to Zone 2, they will first step on the force pressure mat in Zone 1, sit on the bench, and remove their boots. The light on Zone 2 will then activate to indicate the intended destination. The individual will then sit down and rotate in the designated direction, placing their foot on the Zone 2 mat and putting on a new pair of boots. After standing up and waiting for 5 seconds for the system to analyze the individual's PPE and generate an output, the individual will be able to proceed to Zone 2.

The third scenario is when an object is left on the force pressure mats for over 10 seconds. This is important as it could cause an obstruction in the system and unnecessary processing. The light corresponding to the detection mat will blink every 10 seconds until the obstruction is removed.

Although the sensors performed as expected, the system has room for improvement. For example, adding more sensors to the pressure mats to address instances when human presence is not detected due to a failure to touch both sensor strips simultaneously. An infrared proximity sensor with an increased detection range would also be beneficial.

Regarding the results obtained with the visual recognition model testing (Figure 5), the 320x320 trained models performed more efficiently in terms of frames per second and had higher accuracy when compared to the 640x640 models, which had slower detection rates and lower accuracy.

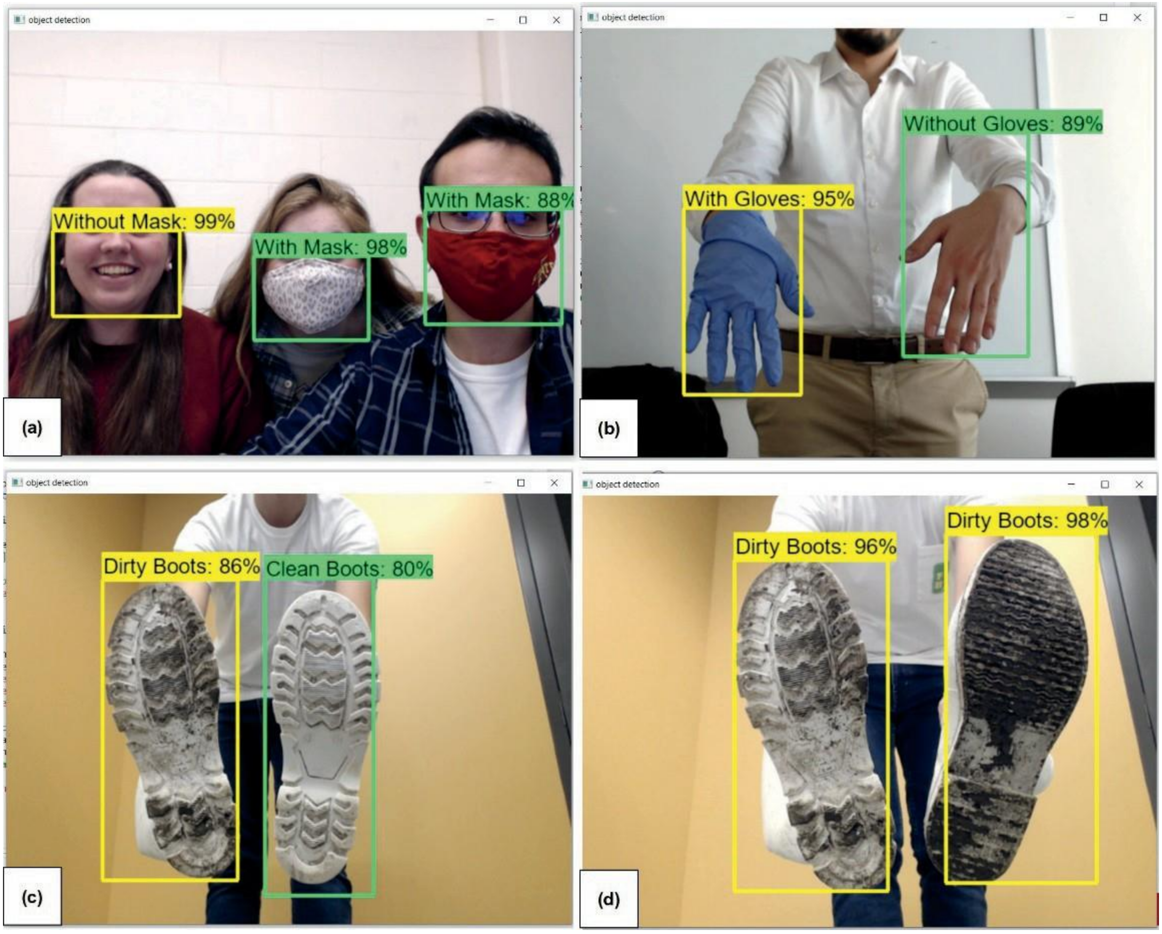

Figure 5: (a) Mask detection on multiple individuals in the same detection frame, (b) gloves detection, and (c and d) image recognition of clean and dirty boots.

However, the accuracy of both 320x320 and 640x640 models for gloves could have been better. This results from the complexity of detecting hands in a human body without using pose estimation detection functions. Therefore, in order to merge the gloves, boots, and face mask detection models, a pose estimation model should be implemented, making it easier for the machine to know where to look for specific details in relation to the overall human body. Additionally, prospective users of this technology have pointed out that making the visual detection system distinguish between farm personnel and visitors' PPE would be useful.

Conclusions

The Danish Entry 3.0, an integrated physical barrier and image detection system, can effectively reduce the risk of pathogen exposure and transmission in livestock production facilities. Through testing, the 320x320 models for boots and face masks were found to be the most efficient in terms of speed and accuracy. However, the 640x640 models for gloves were less accurate, potentially due to difficulty detecting hands within the human body. A pose estimation function is being implemented to improve the overall performance of detection. The Danish Entry 3.0 offers a reliable and cost-effective solution for biosecurity by providing a constant barrier, prompt employee compliance, and data tracking capabilities. It can be used as both an alarm system and an audit mechanism.

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