TOWARDS AN ELECTRONIC SYSTEM FOR ESTRUS DETECTION IN SWINE

BY

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THESIS

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ABSTRACT

Because most pigs worldwide are now bred by artificial insemination (AI), accurate estrus detection is essential. There is consensus that display of the lordosis response (“standing”) following physical boar contact or application of the back-pressure test (BPT) is the gold standard for estrus detection in pigs. However, little research has explored its true accuracy and evaluated whether automated measures could improve upon such a manually driven process. On commercial pig breeding farms, estrus detection relies on multiple trained technicians and daily efforts and occurs year-round. This places an undue burden on an already volatile and limited farm labor supply. And while research into automated technology specific to swine estrus detection is evolving, it remains underdeveloped. Although electronic estrus detection (EED) systems have been successfully integrated into the management of dairy and goat herds, use in swine breeding herds has faced challenges. Therefore, the aim of this thesis is to summarize current knowledge of estrus detection procedures in swine and extrapolate how these processes can be improved using computer vision technology. A YOLOv8 object detection model for distinguishing erect ear posture from neutral ear posture had a mean average precision (mAP) of 98.3% at 0.5 intersection over union (IoU) for all classes. This is acceptable for automatic detection of ear posture in gilts. A YOLOv8 instance segmentation model detected the outline of gilts in single-stall housing with an overall mAP of 99.5% at 0.5 IoU; this model's performance was also satisfactory. A YOLOv8 movement classification model assigning three classes of behavioral responses to gilts receiving the back-pressure test (BPT) showed high false positive rates for one class and high false negative rates for two classes. This model is not yet satisfactory in automatically classifying types of behavioral responses to the BPT. Additionally, a YOLOv8 object detection model was trained to identify four postures (sitting, standing, kneeling, and lying) in prepubertal gilts, achieving an overall average of 0.976 mAP at 0.5 IoU. This model was then applied to a 24-hour dataset of gilts transitioning from proestrus into estrus and metestrus. Time budgets were created for each gilt according to the four postures detected. No statistically significant differences existed among the four postures between pre-puberty and the conclusion of estrus.

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Dedicated to Joe, TJ, Emmie, and Annie.

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CHAPTER 1: REVIEW OF LITERATURE

Abstract

Because most pigs worldwide are bred by artificial insemination (AI), accurately detecting estrus for timing insemination is more important than ever. There is consensus that display of the lordosis response (standing) with physical boar contact or when a human applies the back-pressure test (BPT), are each considered as the gold standards for accurate detection of estrus in pigs. However, very little research has explored its true accuracy and evaluated whether more automated measures could replace and improve upon such a manually driven process. In commercial pig breeding farms, detecting estrus relies on multiple trained technicians and daily efforts, year-round. This places an undue burden on an already volatile and limited farm labor supply. While research into automated technology specific to swine estrus detection is evolving, it is still quite underdeveloped. While electronic estrus detection (EED) systems have been integrated into the management of dairy herds, use in swine breeding herds has faced challenges. Therefore, the aim of this review is to summarize current knowledge of estrus detection procedures in pigs and extrapolate how advances in automated EED in other species could be applied to the development of different systems in pigs.

Introduction

A longstanding obstacle within the swine industry has been its need for and reliance on specialized human labor for many management procedures. While technology like radio frequency identification (RFID) is often used to identify dairy cattle, and pedometers have been used to aid in estrus detection, these have had limited application in the swine industry. There are complexities and other factors that limit their application in pigs, such as type of housing, animal behavior, durability, and meeting the very high fertility measures under the current production systems (Knox, 2016). However, the process of estrus detection in swine is a critical component to high herd fertility, and in sows and gilts, can be characterized as a 1-to-3-day period of sexual receptivity within a 21 estrous cycle. The important aspect of estrus is that it allows for insemination to occur at or near the optimal times for fertilization, whether natural or artificial breeding occurs. Once a female is detected in estrus, ovulation can occur in a wide window of 24 to 72 hours later (De Rensis and Kirkwood, 2016). Because of this, successful estrus detection is a critical part of pork production because it allows for more precise timing for insemination that leads to production of a large litter (Lammers et al., 2007). The standard method for estrus detection in the swine industry is the use of the back pressure test (**BPT**), in which an animal handler pushes on the back and flanks of a female in the presence of a boar to evaluate her reaction (Langendijk, 2001). The standing response (lordosis) is a physical indicator of sexual receptivity in most species. A clear standing response to the **BPT** will be characterized by a frozen posture, arched back, and an ear twitch or erect ears. These symptoms together indicate that the female is in estrus, close to ovulation, and should be inseminated. As the industry has shifted from natural mating to artificial insemination more than two decades ago, accurate detection of estrus has become increasingly vital in appropriately timing artificial insemination for high conception rates and large litter size, efficient utilization of genetically valuable semen, and maximizing labor and financial inputs required for sustainability.

Although producers have relied on the back pressure test for over 50 years (Reed, 1969), its efficacy is under-researched, and better alternatives have yet to see integration into the commercial industry. Because evaluating the standing response relies on the subjectivity of human judgment, and can be altered by environment, stress, and other confounding factors, accuracy in crucial behaviors may be misinterpreted or missed entirely. In dairy cows, over 50% of estrus events are missed, largely attributed to a lack of visual cues from silent estrus (Fauvel et al., 2019). This has prompted experimentation with alternative estrus detection technologies, including pedometers, mount detectors, and electrical resistance measurements. While often initially successful in cattle, these physical detectors of estrus have seen little crossover into the swine industry. Application options are limited due to physical body structure (for example, collars are more practical for dairy cows than pigs) and pigs' proclivities for biting, chewing, or rubbing anything placed externally. Currently, nearly all estrus detection in pigs is visual, and data are lacking on the number of estrus events detected successfully. It is challenging to know the true accuracy of the **BPT** given silent estrus can occur. This occurs on every farm to some degree and is identified when a sow or gilt in estrus does not show a standing response to the back pressure test. Some estrus events are missed due to human error or failure of the animal to display the associated behaviors. While the proportion of missed estrus events is often unknown, preliminary research on electronic capture systems has demonstrated their potential to recognize estrus-positive behaviors that would be otherwise missed (Fauvel et al., 2019; Lee et al., 2019).

Financial returns on swine farms can be impacted by the BPT's accuracy in detecting estrus. In cases where estrus is not detected, animals will accumulate many open days and costs. In cases where estrus is detected late, AI timing may be less than optimal since ovulation windows can be variable, leading to conception failures and low litter size. These scenarios reduce and delay financial returns on the breeding female. Successful AI procedures rely on a once or twice daily estrus detection system inseminations occurring on each day standing. Ensuring that animals receive two inseminations, and on each subsequent day standing is observed, increases the odds that a female will become pregnant (Lamberson et al., 2000). Still, with multiple inseminations, often one of the inseminations will fertilize most of the eggs. This means that the multiple AI approach essentially wastes 50% of the genetic resources and increases costs in semen, shipping, labor, and AI disposables. A more accurate and efficient method of estrus detection could enable farmers to be successful with a single insemination.

A major problem that has faced the industry since the introduction of AI is the need for specialized labor in the manual detection of estrus using the BPT. On average, a farm worker must spend at least 1 to 2 minutes moving the boar to the female, allowing the animals to interact, and conducting the BPT (Knox et al., 2013). This would appear as an inefficient use of limited labor, especially if a faster alternative exists. Additionally, handling a sexually mature boar can be frustrating and dangerous, and therefore, a method of detection that functions without the physical presence of a boar would minimize the need for farms to keep boars on site.

Detection of estrus in pigs can be physically straining on labor, and lead to back, limb, and soft tissue injuries resulting from close contact when pushing, climbing on, leaning over, or sitting on the pigs to detect estrus. When considering that physically manipulating many sows daily throughout the year – sows which often outweigh the technician several times over - it is perhaps not surprising this can lead to problems. The daily need for labor to meet physical demands over an extended period often results in employee burnout and work-related injuries in an already limited labor population. When an industry relies heavily on specialized human labor, it becomes vulnerable to labor market volatility. When the supply of labor decreases, farms rely on fewer employees for more work, leading to burnout and decreased quality of work overall as corners are cut to finish daily tasks. This is especially detrimental to the estrus detection process, which relies on careful observation of often subtle behaviors. The physical process of checking which females are responsive to mating is known as heat check (Knauer et al., 2014). If an employee rushes to heat-check many animals, they may not allocate sufficient time for everyone, potentially missing signs of estrus that could have appeared with a few additional minutes of stimuli.

To create a viable alternative to the **BPT**, a new system would need to meet some or all criteria to: (1) demonstrate superior accuracy when compared to existing methods, (2) function with lower human labor and animal handling requirements, (3) standardize criteria for identifying estrus behavior to avoid subjective disparities, (4) operate at lower cost, and (5) demonstrate broad application throughout the industry. An artificial intelligence model for estrus detection based on computer vision would facilitate continuous monitoring of individual animals, thus capturing behaviors indicative of estrus while lessening a farm's reliance on highly qualified personnel for estrus detection and ensuring this activity could be overseen by less experienced employees. This system may also identify subtle behaviors that may be missed in the narrow timeframe spent administering the back pressure test due to human judgment error or lack of sufficient time to express standing heat.

Precision management is an emerging sector of livestock production that provides technology-based solutions for farmers to remotely capture, track, and analyze large amounts of data on their herds (Berckmans, 2017). While discussion and application of precision livestock farming techniques have increased substantially over the past decade, there is a distinct gap in the research regarding specific applications in swine estrus detection. An in-depth review was conducted of current estrus detection standards in the swine industry, followed by suggestions for the use of precision livestock farming technology to fill these gaps.

Artificial Insemination in the Swine Industry

Artificial insemination (**AI**) is the primary breeding technique used on modern commercial swine farms. In Western Europe, over 90% of sows are bred by **AI** (Gerrits et al., 2005). In the United States, the usage of **AI** exploded from 5% in 1986 to 50% in 1998 (Lamberson et al., 2000). In 2002, the USDA's National Animal Health Monitoring System (NAHMS) surveyed nearly 2,500 swine production sites in seventeen states, accounting for 94% of the US pig inventory. Results from the NAHMS survey indicated more females were bred through artificial insemination than any other technique. Worldwide, over 90% of pigs are bred by artificial insemination (Waberski et al., 2019). Clearly, farrowing rates and reproductive efficiency on most US commercial farms are dependent on the success of that farm's artificial insemination program. Successful **AI** relies on a cascade of factors, including volume of sperm per dose, number of doses per female, and accurate detection of estrus to establish an insemination schedule (Knox, 2016).

The United States' increasing reliance on **AI** over the past thirty years correlates with the expanding size of farming operations. Of all NAHMS surveyed sites that housed at least 500 breeding females, 91.3% utilized artificial insemination, compared to 23.2% in surveyed sites that housed fewer than 250 females. Artificial insemination is the preferred breeding method for most producers due to its economic advantages, diverse genetic options, facilitation of improved health and hygiene practices, and decreased need to house and handle boars (Clapper, 2000). This technique has greatly accelerated genetic improvement in swine through selection differential, in which large quantities of females are inseminated with the sperm of fewer superior sires (Roca et al., 2006). Artificial insemination is also highly efficient; sperm from a single boar ejaculate can breed up to twenty females, a process that would take significantly longer through natural service (Knox, 2016).

In addition to genetic benefits, research also suggests that increased rates of AI are linked to increased farrowing rates and larger litter sizes. A farrowing rate of 85% or better is one success metric for commercial farms, which can be affected by estrus detection, insemination timing, and semen quality (Young, Dewey, and Friendship, 2010).

While successful **AI** has numerous advantages, **AI** failure is a significant problem that can lead to reduced animal production, disrupted animal flow, problems in animal housing, labor scheduling, and increased costs (Lamberson et al., 2000). One source of **AI** failure is inaccurate insemination timing. Artificial insemination doses contain, on average, 1.5 - 4 billion sperm cells, and each female is usually inseminated two or three times (Bortolozzo et al., 2015). Sows checked twice daily for estrus often have higher average economic returns than sows checked once daily, and total performance (quantified by fertility rates and number of piglets born alive) depends on accurately timing insemination with expected ovulation (Lamberson et al., 2000). Administering multiple doses of semen can be an effective strategy to improve the chances of accurately timing estrus closer to ovulation, resulting in high fertilization rates with viable embryos. However, net returns from improved reproductive output are not guaranteed to exceed the extra costs associated with an additional dose.

To decrease the cost of Artificial Insemination, the swine industry must pursue a goal of fewer **AI** doses administered per female per cycle. Most sows are inseminated multiple times per cycle due to variable lengths of estrus and unpredictable sperm viability (Bortolozzo et al., 2015). Sow behavior and employee observations were used to predict optimal insemination schedules, reducing the average number of inseminations on nine commercial farms from 2.3 to 1.35 inseminations per female. The same researchers demonstrated that success from single insemination is possible when the timing is accurate. Indeed, a twelve-hour shift in insemination time can negatively impact conception rates by up to 12% (Germain, Labrecque, and Rivest, 2019). Because preliminary research has demonstrated the success of single inseminations in some populations, an optimal model for electronic detection of estrus would identify preliminary behaviors indicative of estrus prior to visual observation by farm employees. This could facilitate earlier insemination, fewer additional doses per animal, and improved conception rates.

When a female is in estrus, her expression of estrus-positive behaviors determines if and when she will be inseminated (Kemp et al., 2005). The goal for producers should be twofold: 1) detecting estrus as early and accurately as possible and 2) inseminating with the fewest doses of semen needed to create a viable pregnancy that ends with the farrowing of a large number of live piglets.

Estrus detection may be achieved earlier within a female's cycle if she is continuously monitored. While 24/7 in-person monitoring is not feasible given the large herd sizes and high employee turnover on many farms, continuous camera monitoring is both affordable and widely accessible for many producers. Machine-learning models of estrus detection are designed to analyze individual pig behavior 24/7 and may provide information about behavioral changes in real-time (Cowton et al., 2019; Nasirahmadi et al., 2017; Zhang et al., 2019). This is a significant advantage over current estrus detection methods, in which farm laborers have one or two scheduled windows per day to evaluate all eligible females, often amounting to 1 - 2 minutes per animal. This short window can be sufficient for females reacting to the back pressure test immediately with a strong estrus-positive response but can miss animals who display subtle behaviors or demonstrate a delayed response. Because commercial farms are limited by available human labor, they have, in turn, a limited amount of time to spend observing each animal. A missed opportunity for insemination delays the farm's breeding schedule and affects the producer's bottom line. This occurs when labor investments are made on a healthy animal whose estrus is missed and, therefore, is not inseminated in time and does not farrow on the same timeline as the rest of the inseminated females.

Current Standards of Estrus Detection

Research tracing the origins of the back pressure test is lacking, though published mentions of this assessment as a measure of estrus detection appear as early as the late 1960s and early 1970s (Signoret et al., 1975; Bristol et al., 1971; Reed, 1969). Sixty percent of sows in estrus will stand for the back pressure test without the presence of a physical boar; the response rate increases to 90% with the addition of boar pheromones and auditory stimulation. Including fence-line contact with a physical boar, estrus expression reportedly increases to 100% (Kemp et al., 2005). While 100% expression may occur in research conditions or other isolated groups and would facilitate highly accurate insemination schedules, this figure is not representative of all farms when accounting for silent estrus or the large size of commercial farms. A sow or gilt in silent estrus is a cyclical animal that ovulates without exhibiting behaviors visibly indicative of estrus, such as lordosis or erect ears (Stancic et al., 2011). A female exhibiting silent estrus would not be positively identified by the back pressure test despite nearing ovulation (Belstra et al., 2007).

Estrus expression is a spectrum, with responses indicative of no estrus (vocalization, movement away from stimulus, extrication from touch) on one end and the confirmed standing response on the other end (lordosis, erect ears, swollen vulva, lack of vocalization) (Knox et al., 2015; Van Eerdenburg et al., 2002). False positives, or females who stand for the back pressure test but lack the follicular growth that precedes ovulation, are possibly low or unknown. Such follicular growth is typically characterized as a follicle that evolves from 2 – 4 mm in diameter at the onset of the follicular phase to 7 – 8 mm in diameter just prior to ovulation (Soede et al., 2011). And while false positive responses to the back pressure test are rare, false negative responses – so-called “silent estrus” – are more common and have greater repercussions on the industry, especially in gilts, and sows that may be bred while still nursing (Dovc et al., 2010). And between these strong positive and strong negative responses exists a gray area that may be difficult to visualize or interpret, resulting in more false negatives. With use of ultrasound to evaluate follicles on the ovaries, females that exhibit follicular growth may still respond negatively to the BPT. Alternatively, they may exhibit a more neutral or intermediary response by standing quietly for the **BPT** without erect ears or the full lordosis response. Estrus detection is dependent on visual cues displayed by the female, and variation in these independently or collectively can cause uncertainty and result in misinterpretation.

Alternative Approaches

A potential confounding issue with alternative estrus detection technologies is the use of the BPT as a metric of accuracy in developing the product or research. Clark et al. (2011) used infrared thermography to measure changes in vulvar skin temperature of 25 gilts and 27 sows during estrus. The study demonstrated that vulvar skin temperature changed significantly during estrus, suggesting the use of digital infrared thermography as a complementary tool in assessing estrus. However, females in the study were only subjected to ultrasound and temperature recordings if they exhibited a standing response to the BPT. While this may be a useful tool for females displaying a strong estrus-positive behavioral response, it omits animals with follicular growth who do not show a strong standing response. The mammalian estrous cycle is divided into four phases: proestrus, estrus, metestrus, and diestrus. These phases define the preparatory, ovulatory, luteal regressive, and sexually inactive portions of the estrous cycle, respectively. Sykes et al. (2012) used digital infrared thermal imaging to evaluate vulva temperature in 32 gilts and delineate metestrus and diestrus phases. The researchers proposed that estrus detection through thermal imaging could catch females in silent estrus. Like the previous study on vulva temperature, this group of gilts was exposed to a teaser boar and observed for signs of estrus. Gilts were subjected to thermal imaging of the vulva at the time of the first standing estrus and again ten days later. The study concluded that gilts in estrus had higher average vulva surface area temperatures than gilts in diestrus. The initial results of the study, combined with the non-invasive nature of the thermal imaging process, make this a promising addition to current estrus detection tools. However, unlike Clark et al. (2011)'s study, researchers did not use ultrasound on the gilts to confirm follicular growth before or after standing heat. So, while the study proposes using this imaging tool on animals exhibiting silent estrus, its methods facilitated use on gilts expressing standing heat exclusively. Had researchers verified the existence of follicular growth (or lack thereof) with transrectal ultrasound following boar exposure, they may have identified one or more gilts who did not stand for the back pressure test but continued to grow medium to large ovarian follicles, indicating silent estrus. It is still quite possible that digital infrared thermal imaging could be used to detect silent estrus, but this has yet to be applied directly. Ultimately, the application of digital infrared thermal imaging on animals in silent estrus (or those displaying weak behavioral responses to the **BPT**) is unknown.

The Limitations of Farm Labor

Current methods of swine estrus detection rely heavily on human labor, especially when animals are housed in groups. Estrus detection in group housing with a teaser boar usually requires two people, one to handle the boar and another to conduct the back pressure test. After an initial fence line interaction between the boar and female, a farm laborer rubs the female's back, attempting to provoke lordosis. If the response is ambiguous or does not exist, the employee progresses to pushing and even sitting on the female, mimicking the pressure of a boar mount (Knauer et al., 2014). This process quickly becomes strenuous for the laborer tasked with rubbing, pushing, and sitting on dozens or even hundreds of animals in a row.

Because the use of AI requires boars on the farm, it also requires specialized human labor to interact and manage the boars. Rising farm wages and lessened availability of migrant workers from Mexico have contributed to the tightening farm labor market (Zahniser et al., 2018). The Covid-19 pandemic ravaged the agriculture industry, infecting workers, forcing widespread shutdowns, and depleting the labor supply. Farms and meat packing plants became immediate hotspots of virus transmission, and the agricultural sector reflected one of the highest outbreak rates of all industries (Murti et al., 2020). From March 1, 2020, to March 31, 2021, agricultural producers and laborers accounted for up to 9.5% of all Covid deaths in the United States (Lusk et al., 2021). In April and May 2020, daily slaughter volumes of pigs and cattle plummeted as much as 40% compared to the equivalent period in 2019 (Lusk et al., 2021).

Employee turnover is an additional contributor to the volatility of the agriculture labor market. Average yearly turnover (percent of total turnover among full-time positions) was 92% in eleven North American commercial swine farms recently studied, with high turnover rates for nearly all surveyed operations (Black et al., 2021). In comparison, the 2017 animal caretaker turnover rate for US swine farms was estimated between 20 and 35%, according to the National Pork Board (2017). Although high turnover is expected in the industry, it is expensive for producers and can decrease overall productivity. Costs associated with a turnover event include recruiting, hiring, and training a replacement as well as opportunity costs associated with interrupted productivity. These costs can be estimated at 30 - 150% of the employee's salary (Hinkin et al., 2000; Boushey et al., 2912; Park et al., 2012; Moore, 2012; as referred to in Black et al., 2021). And while turnover is not exclusive to the swine industry, its effects are magnified due to the sheer number of workers employed. As one of the largest pork exporters in the world, the US housed nearly 60,000 swine operations in 2021 and was responsible for approximately half a million jobs in all facets of the production system (Gialva, 2014; Work in Pork, 2021). With such a large industry that employs hundreds of thousands of employees, constant labor turnover interrupts production, increases labor costs, and negatively impacts animal welfare and reproductive outcomes. The effect of a turnover event on production was assessed two months after the onset of the turnover event (Black et al., 2021). Employee-mediated voluntary turnover has been associated with decreased production for two parameters: number of pigs weaned per sow (**PWS**) and pre-weaned pig mortality (**PWM**).

The Covid-19 pandemic and subsequent shortage of migrant workers have highlighted how quickly the swine industry can be affected by volatility in the labor market.

Current Precision Livestock Farming Technologies in the Swine Industry

The world population is expected to surpass 9 billion people by 2050, and agricultural producers must optimize production to feed that population (United Nations, 2017). Strategies for optimizing production lie in precision management, an emerging sector of livestock production that equips producers with technology to remotely capture, track, and analyze large amounts of data on the welfare and production efficiency of herds too large to individually monitor at regular intervals. One goal of precision livestock farming is to achieve continuous, fully automated monitoring of animals (Tzanidakis et al., 2021). This can be accomplished in numerous ways, such as image and video-based capture systems. These are quickly emerging as some of the most popular, effective, and broadly applicable technologies (Kakani et al., 2020; Lovarelli et al., 2020; Neethirajan et al., 2021).

Precision livestock technologies have been used to conduct continuous welfare assessments, subsequently detecting deleterious behaviors (such as tail biting or piglet crushing) and notifying producers promptly upon detection. As the number of individual farms decreases and the number of animals per farm increases, producers lose the ability to manually monitor individual animals for signs of stress or discomfort. By the time an animal has elicited a bio-response in the form of behavioral change, the impact of that stress has already occurred (Berckmans, 2017). A pervasive goal of livestock production is minimizing the stress experienced by each animal. Stress responses can diminish performance in multiple areas, including immune function and response, feed intake, and reproductive performance (Manteca et al., 2013).

Varieties of precision livestock technology include 2D and 3D cameras for evaluating behavior and physiology; microphones for analyzing sound patterns; thermometers and infrared imaging to assess health status; accelerometers to track movement patterns; radio frequency identification (**RFID**) tags; and facial recognition software (Benjamin et al., 2019). Multiple types of precision livestock technologies may be integrated to improve the overall accuracy and efficiency of estrus detection.

Computer Vision in Precision Livestock Farming

Although current research on swine estrus-specific applications with precision livestock farming is limited, several continuous capture systems have shown promise in improving behavioral recognition of individual animals of various livestock species including cows and goats (Wang et al., 2013; Vayssade et al., 2023). A fundamental component of these systems is the ability to automatically identify individual animals and distinguish them from others in the herd. Deep learning methods that detect individual pig faces and/or bodies can be used as a tool to objectively evaluate pig health and behavior. Convolutional neural networks (CNN) can be used to automatically detect individual pig faces and eyes; when such an algorithm was applied to 10 randomly selected pigs, results showed 83% accuracy in assessing 320 images (Marsot et al., 2020). The study was limited by the relatively low number of test images, and most false positives erroneously confused open mouths, snout openings, or dirt spots for eyes. However, this approach demonstrates the ability of deep learning models to track individual identifiers, tackling the first step in automated livestock assessment. Because estrus detection relies on physical cues from the animal's ears, head, and back, individual identification and behavior recognition are essential components of the process.

Four types of video-based behavior recognition include (1) postural, (2) locomotive, (3) area-related, and (4) interactive (Yang et al., 2020). Video-based models of behavior recognition rely on two techniques: segmentation and detection. Segmentation stratifies the outline of an individual pig using pixels to distinguish that outline from the background image. Detection locates each pig within a rectangular area (bounding box), which may contain parts of the background, according to the pig's features. These features are critical for object detection and include color, texture, and shape. Pig segmentation “is the basis for analyzing the body size, weight and posture of pigs” (Yang et al., 2020).

Further, 2D and 3D imaging systems can effectively identify pig behaviors and improve livestock production (Arulmozhi, 2021). Proposed benefits include improved production efficiency and performance, earlier disease detection, better environmental management, increased sustainability, and more robust data collection and data analysis of individual animals. The affordability, widespread availability, and ease of use of camera sensors make them ideal for achieving these outcomes. Camera sensors allow producers to monitor pigs closely and accurately at an affordable price – a necessary feature when looking for potentially subtle signs of estrus that may come and go quickly. One notable drawback is that many producers lack comfort and experience utilizing targeted software systems to analyze the camera images. Cameras are one static piece of a robust computer vision system, and they are minimally useful without accompanying software to analyze and interpret the resulting images. Additionally, camera placement must be carefully considered when monitoring group-housed pigs. Occlusion is a common problem in which poles, feeders, or other objects (including other animals) disrupt the camera’s view of an animal. This is more likely to happen in group-housing scenarios due to the variable number of objects in each pen, so thought must be given to placement in which the least amount of visual obstruction is likely.

Threshold segmentation can also serve an integral function in the process of detecting individual livestock within a video frame. Using cattle as a model, animals were segmented from their background, and a Mask R-CNN deep learning framework was applied to detect the cattle in motion, enhance the images, and perform body contour extraction (Qiao et al., 2019). Results showed that the Mask R-CNN approach resulted in a Mean Pixel Accuracy of ninety-two percent. Individual detection is often valuable for cattle farmers for feedlots or chutes when accounting for overlapping animals. In the swine industry, this approach can also help detect behavioral differences or anomalies amongst group-housed animals.

Additionally, computer vision applications can be refined to detect more specific behavioral anomalies in individual animals. Because lameness is a common condition in cattle that causes pain and affects locomotion, health, welfare, and productivity, it is in a producer's best interest to be aware of a lameness problem early so that the problem can be addressed promptly (Cramer et al., 2023). Much like estrus detection in pigs, lameness in cattle is assessed visually, with behavioral indicators including a reduction in walking speed, alteration to walking pace, arched spine, and lowered head when walking (Alsaaod et al., 2019). A review by Qiao et al. (2021) explored the ways that precision livestock farming can autonomously improve lameness detection by providing a means for real-time continuous welfare monitoring, ultimately improving cattle productivity. Sensor options include force platforms, 2D and 3D cameras, and wearable accelerometers. These sensor measurements – which included vertical kinetic leg force, walking speed, and laying time - were used in algorithms to generate lameness traits such as step overlap or back curvature. Purported benefits of these automatic electronic lameness detection systems included more objective, consistent assessments (Gardenier et al., 2018). This is applicable to similar thematic struggles within the swine industry regarding the estrus detection process.

Developments in Electronic Estrus Detection

Various computer vision applications have seen early adoption and even success in the cattle, sheep, and goat industries. Potential uses have been proposed since the 1990s, and several studies have shown preliminary success with dairy cow models (Blair et al., 1994; Senger, 1994). An "ideal" estrus detection system for dairy cattle would improve efficiency rates when compared to visual detection. Proposed requirements for this system, as suggested in 1994 by P.L. Senger, stipulate (1) continuous cow surveillance, (2) accurate and automatic identification, (3) long-lasting operation, (4) low or no labor inputs, and (5) accuracy rates of at least 95% in correctly identifying behaviors correlated with ovulation. While it has taken over a decade to develop and implement technology in line with such a framework, today's precision livestock technologies (**PLT**) may align with these standards.

Image processing and artificial intelligence can be used to develop non-invasive, non-contact methods of estrus detection in dairy cattle, thus removing human bias from the visual assessment of estrus-type behaviors (Arrago et al., 2020). Two custom convolutional neural network (CNN) models were trained to visualize bounding boxes of predicted cow objects and verify if overlapping boxes constituted activities of estrus. Using top-view cameras, researchers monitored seventeen cows, one bull, and one water buffalo. TensorFlow Object Detection API software was used to localize and identify multiple objects in an image frame. Results indicated significant variations in confidence scores between individual animals, and estrus events were detected at an efficiency rate of 50%. While this preliminary trial suffered from low-efficiency rates, several impacting factors were identified, including "trade-offs between speed and accuracy," the limitations of identifying individual animals based on coat pattern, and the need to define additional estrus detection criteria.

A similar study (Noe et al., 2020) has reduced system costs by using image analysis alone. For that, two primary behavioral signs of estrus are mounting and following; these behaviors were tracked, and the results were used to compare the efficacy of three supervised machine learning methods [Support Vector Machine (SVM), Logistic Regression (LR), and Multiple Linear Regression (MLR)]. Using a dataset of 2265 color images, results indicated that SVM outperformed LR and MLR with accuracies of 97%, 94%, and 94%, respectively, when detecting the primary behaviors. Notably, the researchers assessed estrus using two behaviors and did not track other primary or secondary signs of estrus, such as restlessness, swollen vulva, or mucosal discharge.

Non-visual methods of estrus detection were examined in cattle and compared in 2002 by Rorie, Bilby, and Lester. The three methods tested were pedometers, electrical resistance measurement, and mount detectors. Cattle in estrus are three to four times more active at the onset of estrus; thus, pedometers are used to track individual animals within a herd and single out those individuals with higher-than-average activity levels (Reimers et al., 1985). The researchers concluded that pedometers were more accurate when combined with visual observation for the detection of heat. Intravaginal resistance probes, designed to measure changes in reproductive tract secretions, were considered the least practical method due to their high labor requirement. Mount monitors, used to track the number of times an animal is mounted within a four-hour period, displayed the broadest application for dairy cattle by detecting 100% of heifers in heat.

While there are a variety of precision livestock tools both in development and currently on the market, an important piece of the conversation is weighing the benefits and downsides of invasive devices with less invasive technologies.

On the most invasive end are surgically implanted bioimpedance devices, which have been inserted vaginally in dairy cattle and rely on body temperature to assess and predict the different stages of an animal through its estrous cycle. While they have displayed promising accuracy in small research trials, because they are implanted surgically under anesthesia, these devices are the most invasive option and not cost-effective for large farms (Miranda et al., 2009).

While considered somewhat invasive, wearable sensors can be administered quickly and easily to an upright animal without the need for anesthesia or pain medication and without obstructing the animal's natural movement patterns. Inertial Measurement Unit (**IMU**) sensors, such as those worn commonly on the neck or ears of dairy cattle and sheep, measure activity in the field and can be a cost-effective measure for large herds. In recent years, they have also become a more attractive and attainable option for farmers in less developed countries (Parikesit et al., 2013).

Another non-invasive option on the opposite end of the spectrum is measuring acoustic vocalization. Several preliminary studies have analyzed different acoustic features of water buffalo sounds, such as call duration, amplitude, and mean pitch, to determine a potential correlation with the onset of estrus. In a sample of 20 Murrah buffalo, call duration during proestrus and metestrus phases of the estrous cycle was notably prolonged compared to other phases (Devi et al., 2016). Vocal intensity was also much higher in proestrus than in other phases, while pitch was found to be highest during metestrus. While this research is still preliminary, and many questions are yet to be answered, the authors suggest that this may be a valuable metric for detecting asymptomatic estrus, which is a recurring problem in the swine industry. However, because it is so preliminary, it is difficult to imagine what this system would look like as a commercial tool or interface allowing producers to interact with their herd's results, especially in large group settings.

While image-based capture systems have shown promise in certain applications of swine production, such as monitoring eating and drinking behavior and identifying aggressive interactions in group housing, the extension of these systems into estrus detection is underdeveloped. Estrus detection in pigs is highly subjective, with human laborers responsible for evaluating individual responses to the back pressure test. Pigs are limited in their natural expression of estrus due to body type and housing structure. Unlike cattle, whose estrus behaviors are expressed spontaneously via mounting and following other members of the herd through open fields, many female pigs are housed in individual stalls. Stall-based housing limits social interactions between females; therefore, estrus-positive behaviors that may be seen in group housing are lacking. This renders the **BPT** the sole opportunity for workers to observe estrus responses in females. An electronic capture system using image segmentation would allow producers to monitor their herds 24/7 and alert to estrus-correlated behaviors outside of back pressure assessments.

One currently available commercial product that aims to address this problem is Ro-Main's smaRt Tracking system. Comprised of a network of surveillance cameras, the Ro-Main system processes and analyzes images of sow posture and behavior in real-time, exporting the information to a user interface that alerts producers to optimal breeding times based on sow behavior (Labrecque et al., 2019).

Additionally, a Belgian study by Verhoeven et al. (2023) employed the Ro-Main smaRt Tracking system on three farms, following a total of 6717 sows over three years (18 months before implementation of the system through 18 months post- insemination). Metrics followed included farrowing rate, percentage of repeat breeders, farrowing rate after first insemination, and number of piglets born per litter. Results were variable between farms, but Farm A experienced notable increases in all metrics following the implementation of the Ro-Main system. Farm B saw a decrease in the number of piglets born per litter with the caveat of an insufficiently low insemination dose, and Farm C's metrics remained mostly constant.

Thermal imaging cameras have also been used as a non-invasive visual means to measure changes in vulvar skin temperature of both gilts and multiparous sows to determine whether temperature changes correlate with the onset of estrus. A study by Clark et al. (2011) of 25 gilts and twenty-seven sows showed that thermographic imaging detected a rise and subsequent fall in vulvar skin temperature several hours before ovulation, which may be helpful when paired with an existing conventional method of estrus detection such as boar exposure. While this remains an attractive non-invasive option, it is not yet validated as a stand-alone option for estrus detection.

Conclusion

Existing literature has established the critical importance of accurate estrus detection in successful swine insemination, but methods to achieve and improve the accuracy of detection are under-researched. For over 50 years, the industry standard for assessing heat has been the back pressure test. Interestingly, despite highly variable accuracy rates (Alvarenga et al., 2006), intensive labor requirements, and ineffectuality when used on animals in silent estrus, there is little published research proposing alternative methods.

Precision livestock farming (**PLF**) strives to provide continuous, real-time data to producers of large herds incompatible with individual monitoring. Advances in PLF technology have already benefited the dairy industry. Automated methods of estrus detection, such as pedometers, mount detectors, and electrical resistance measures, have laid the groundwork for more advanced techniques that may one day rival the accuracy of visual detection but with lower costs and reduced labor inputs. While the physical detectors used in dairy studies may lack practical application with swine, the software used to analyze these metrics remains transferable.

The swine industry has aggregated multiple applications of PLF, and cameras have been used with image segmentation to monitor feed and water intake and incidences of piglet crushing, with the overarching goal of improving animal welfare.

This review has addressed a significant gap in the existing literature, highlighting the variability of the back pressure test. While current precision livestock systems have primarily seen integration in cattle systems, there are opportunities for computer vision-based systems to see a practical application in the swine industry, particularly in estrus detection. A computer vision system of estrus detection using an electronic capture system can potentially be utilized as a more cost-effective, labor-efficient alternative to existing estrus detection methods, such as the back-pressure test.

CHAPTER 2: A COMPUTER VISION MODEL FOR CLASSIFYING MOVEMENT IN PREPUBERTAL GILTS

Abstract

Because most pigs worldwide are bred by artificial insemination, accurately timing estrus is essential in predicting an animal's ovulation window and ultimately achieving a successful pregnancy. Determining the exact time of ovulation is difficult, so most producers assess animals for estrus using the back-pressure test (BPT). However, conducting the BPT is often time-consuming, and an animal's reaction to the assessment can be subtle or difficult to interpret. Although the BPT is subjective and prone to error, it can be improved with computer vision technology that autonomously measures animal movement. The aims of this thesis research were to 1) assemble a dataset of images capturing stall-housed gilts during the BPT, 2) create a movement classification model using YOLO (You Only Look Once) model to correlate the degree of animal movement with three categories of BPT responses, and 3) test a movement detection model on the dataset of stall-housed gilts to automatically identify three categories of BPT responses. Digital images of gilts from pre-puberty through completion of the first estrus were segmented using one class of image ("pig"). A model was then trained on the images using YOLOv8, achieving an overall mean average precision (mAP) of 0.995 at 0.5 intersection over union (IoU). The resulting model was applied to a dataset of images containing stall-housed gilts receiving the BPT. This model was used to determine how much an animal moved during the BPT when in estrus vs not in estrus. Although the model achieved high accuracy in automatically detecting the presence of gilts in a stall, the resulting movement detection model showed substandard performance in distinguishing the three categories of BPT responses.

Introduction

The swine industry has long been constrained by its dependency on specialized labor, especially in the reproductive sector. Artificial insemination (AI) is used by over 90% of swine production systems worldwide (Waberski et al., 2019), engendering emphasis on accurate estrus detection and insemination timing.

For over fifty years, the standard method of estrus detection in pigs has been the back-pressure test (BPT), a visual assessment of a female's receptiveness to mating. The BPT often begins with fence line exposure between a female and an on-site boar. After an initial contact period, a farm laborer will begin to push on and rub the flanks of the female to provoke a reaction (Langendijk, 2001). If a female responds to the BPT by freezing, arching her back, perking her ears, and/or remaining silent, then she is said to have a strong standing response. This strong response allows the producer to assume the likely start of ovulation, which is typically within 48 hours of the first positive response to BPT. The anticipated date of ovulation will then determine that animal's insemination schedule. Thus, accurate estrus detection is critical in the timing of artificial insemination.

Although the industry has relied on the back-pressure test as early as the late 1960s and early 1970s (Reed, 1969 and Signoret et al., 1975), it is not infallible. A central problem with the BPT is its reliance on subjective judgment. Because there is not a universally standardized metric with which to evaluate the BPT, and because assessment of the test relies on human judgment, it is liable to misinterpretation. Additionally, an estrus response is not always a binary yes or no. Some animals exhibit a so-called weak response, with mixed attributes of positive and negative tendencies.

Currently, few systems exist to automatically evaluate a pig's response to the BPT. An automatic system for detecting estrus would need to: (1) demonstrate clear accuracy and (2) detect ambiguous or weak behavioral responses. Our hypothesis is that gilts in estrus will engage in less movement during administration of the BPT, allowing a segmentation and movement classification-based computer vision model to automatically assess whether an animal is in estrus or not based on their reaction to the BPT.

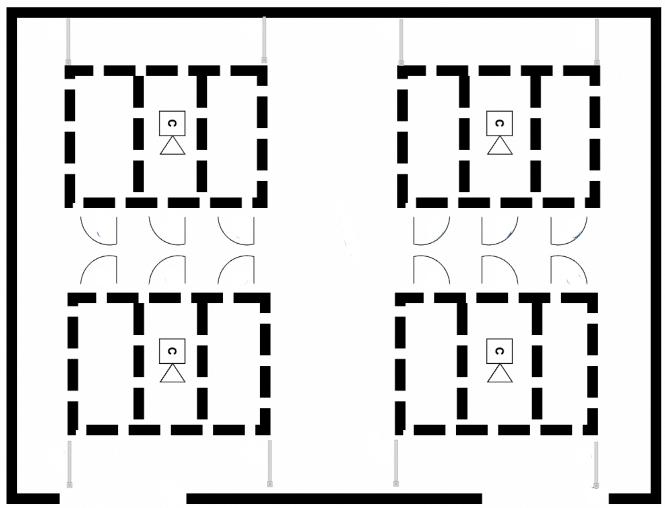
This thesis sheds light on the need for supplementary technology to assist swine producers in the estrus detection process. We suggest a computer vision approach that may contribute to this objective.

Materials and Methods

Animal and Housing Specifics

This study was conducted at the Swine Research Center (SRC) at the University of Illinois in Champaign, Illinois. Images were collected from five populations of Yorkshire x Landrace gilts between April 2022 and September 2022. All gilts were prepubertal and age-matched within replicates. Ages ranged from 168 to 180 days at the start of each replicate. Animals were housed in single-stall confinement, and stalls were arranged in groups of three (Figure 1). Animals were fed once daily and had *ad libitum* access to water.

Figure 1. Diagram of the room configuration at the Swine Research Facility. One Microsoft Kinect camera is centered over each cluster of three stalls and affixed to the ceiling. During the back-pressure test, the boar enters from the bottom right and proceeds around all stalls in a clockwise fashion.



Images for the first replicate, containing five gilts, were collected over a period of five days. The second and third replicates contained six gilts each and were followed for six and seven days, respectively. The final two replicates each contained twelve gilts followed for six days. Images were recorded once daily during the administration of the back-pressure test.

Data Collection

Four Microsoft Kinect V2 cameras were installed at SRC to capture image data. Each group of three stalls was recorded by one camera, which was centered and attached to the ceiling. Digital color images were captured at one-second intervals and later converted using an image acquisition program created in MATLAB.

PG600 was administered on day zero of each replicate to synchronize estrus. In the first replicate, two gilts received PG600 as part of the treatment group. In replicates two and three,

three of the six gilts were injected with P6600. In replicate four, six of twelve gilts received the treatment, and in the final replicate, all twelve animals received the treatment. The latter decision was made to maximize the number of gilts exhibiting strong positive behavioral responses to the back pressure test. All forty-one gilts were exposed to once-daily fence line contact with a boar while the back-pressure test was administered by members of the research team.

All five replicates used transrectal ultrasound on day 0 to determine which gilts would be part of the PG600 treatment group. These ultrasounds established baseline measurements for ovarian health and follicular growth. On day 4, all gilts again received transrectal ultrasounds to measure follicular growth and confirm ovulation. Animals who showed ovarian abnormalities on day 0 were excluded from the treatment group and did not receive PG600.

Notes describing each gilt's response to the back-pressure test were recorded on a paper log. Replicates were followed until all gilts injected with PG600 returned to negative displays of estrus. This was to ensure the collection of data before, during, and after estrus, and accounts for the variable length of each replicate.

Data Analysis

Top-view images from forty-one gilts were labeled using LabelStudio, an open-source data labeling platform. Five hundred images, each containing three gilts, were segmented and assigned one class name ("Pig"). Outlining each animal in the image allows the computer to apply a "mask" and extract its exact shape, distinguishing it from other items in the background. Labels and images were exported in YOLO format to facilitate model development. This dataset was then used to train and validate an Ultralytics YOLOv8 instance segmentation model. 80% of images were used to train the model and the remaining 20% for validation. The instance segmentation model was trained for 30 epochs.

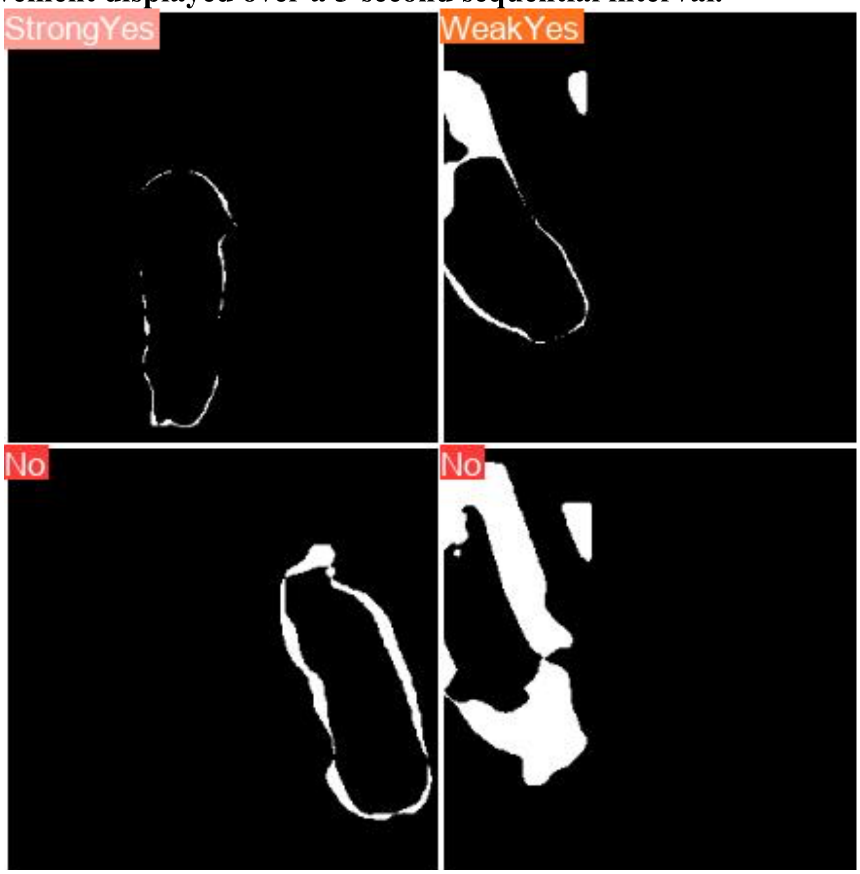
Next, three BPT behavioral responses were defined: *Strong Yes*, indicated by a locked back and erect ears; *Weak Yes*, indicated by a combination of locked posture and relaxed ears *or* erect ears with some degree of bodily movement; and *No*, characterized by relaxed ears and extrication from touch (Table 1). The dataset of forty-two gilts was searched for examples of all three behavioral responses. Because the *Strong Yes* response occurred less often than the *Weak Yes* and *No* responses, an effort was made to maximize the number of examples from this category. Over 300 images of the *Strong Yes* response were collected. The shortest video clip demonstrating this response was seven frames in duration; thus, the three hundred images were divided into short videos each containing seven sequential frames. The frame rate was one image per second. Therefore, the resulting video clips were seven seconds in length. The same process was applied to videos of *Strong Yes* and *No* responses, resulting in (44) seven-frame videos for each of the three behavioral responses.

Table 1. Ethogram of back-pressure test behavioral responses, for use in image labeling

Image Class	**Description**
Strong Yes	Animal stops moving and arches back with erect ears that are flush to head
Weak Yes	Animal stops moving and arches back with flaccid ears *or* animal exhibits slight movement with erect ears that are flush to head
No	Animal extricates from touch with flaccid ears

This collection of videos was used to train a new YOLOv8 segmentation model that pulled mask activity at five-frame intervals. The intervals chosen were 1st and 5th frame, 2nd and 6th frame, and 3rd and 7th frame. The resulting image revealed the amount of movement exhibited between the start and end of each interval (every five seconds), reflected in the amount of white seen in each image. As seen in Figure 2, images of animals displaying the *Strong Yes* response are faint, empty outlines on a black background, whereas images of animals exhibiting the *No* response reveal partially or fully filled outlines.

Figure 2. Predicted responses to the back-pressure test, resulting from an image classification model run for 30 epochs. The white mask in each image represents the amount of movement displayed over a 5-second sequential interval.



Finally, a YOLOv8 classification model was run for 30 epochs on the previous dataset and contained three class names: *Strong Yes*, *Weak Yes*, and *No*. The objective of creating this model was to automatically assess behavioral responses to the BPT.

A supplementary detection model was also created in YOLOv8 to identify instances of erect ears. Bounding boxes were drawn around the ears of gilts in LabelStudio. Each of the 287 images contained at least one gilt displaying vertically perked ears that were flush to the head, often with a visible entry to the ear canal. One of two labels was assigned to each bounding box: "ears erect" or "ears neutral." A YOLOv8 detection model was trained on the images, with 80% reserved for training and 20% for validation. The model was run for 10 epochs.

Mean average precision (mAP, equation 1) and intersection over union (IoU, equation 2) were reported for each model. Additionally, calculations were conducted for positive predictive value (PPV, equation 3); negative predictive value (NPV, equation 4); sensitivity (equation 5); specificity (equation 6); precision (equation 7); recall (equation 8); accuracy (equation 9); and error (equation 10).

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i (2) \qquad [1]$$

where
mAP = mean average precision
AP = average precision
N = number of classes

$$IoU = \frac{|A \cap B|}{|A \cup B|}(1) \qquad [2]$$

where
IoU = intersection over union
A = area of label box
B = area of predicted box

$$PPV = \frac{True\ Positive}{True\ Positive + False\ Positive} \qquad [3]$$

$$NPV = \frac{True\ Negative}{True\ Negative + False\ Negative} \qquad [4]$$

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \qquad [5]$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \qquad [6]$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad [7]$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad [8]$$

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Negative + False\ Positive + True\ Positive + False\ Negative} \quad [9]$$

$$Error = \frac{False\ Negative + False\ Positive}{True\ Negative + False\ Positive + True\ Positive + False\ Negative} \quad [10]$$

Results and Discussion

Model Training

Trained at 30 epochs, the initial single-class segmentation model achieved a mean average precision (mAP) of 0.995 at 0.5 intersection over union (IoU). Because a desirable outcome for both mAP and IoU is close to 1.0, this model was considered successful in segmenting individual pigs within single stalls. A sample of the segmented images is shown in Figure 3.

Figure 3. Example of animals segmented for movement classification. The solid green masks can be extracted separately from the background image.

The movement classification model, trained at 30 epochs, had positive predictive values (PPV) of 1.0, 0.60, and 0.67 for the *Strong Yes*, *Weak Yes*, and *No* classes, respectively. Negative predictive values for the *Strong Yes*, *Weak Yes*, and *No* classes were 0.75, 1.0, and 0.83, respectively. The accuracy and error rates for all classes were 77% and 22%, respectively. The *Strong Yes* class had a sensitivity and recall of 0.33; specificity of 1.0; and precision of 1.0. The *Weak Yes* class had a sensitivity and recall of 1.0; specificity of 0.66; and precision of 0.6. Lastly, the *No* class exhibited a sensitivity and recall of 0.66; specificity of 0.83; and precision of 0.66. A confusion matrix of the results is shown in Figure 4, and the amount of loss experienced in model training and validation is presented in Figure 5.

Figure 4. Amount of loss reported from the movement classification model. A model that predicts perfectly has zero loss.

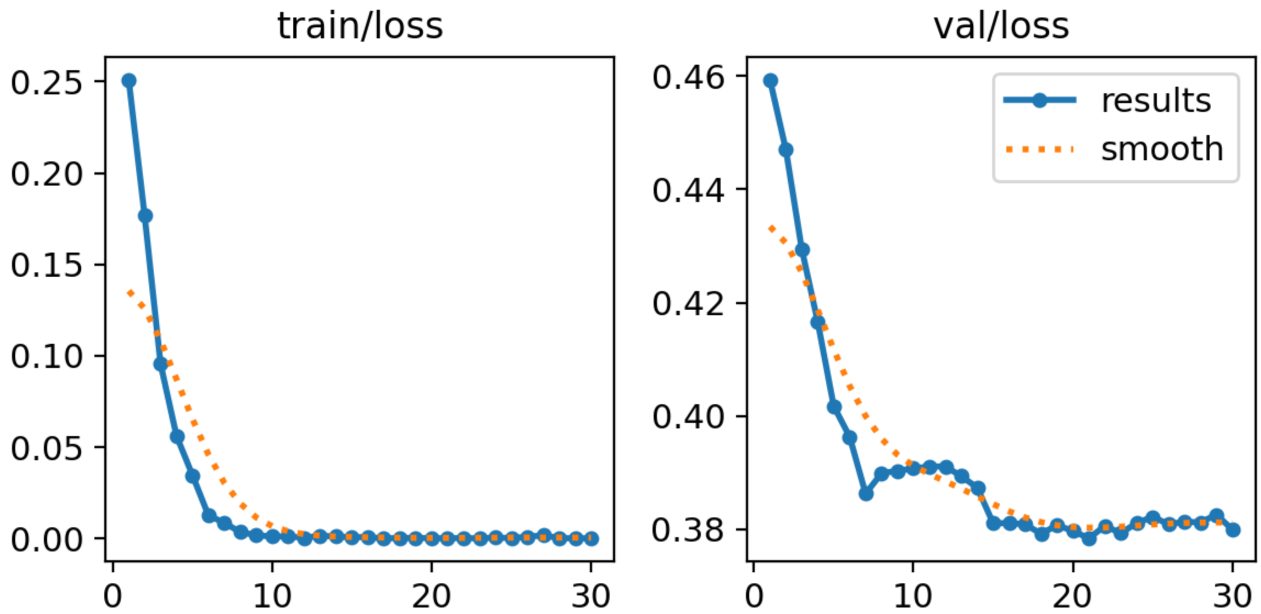
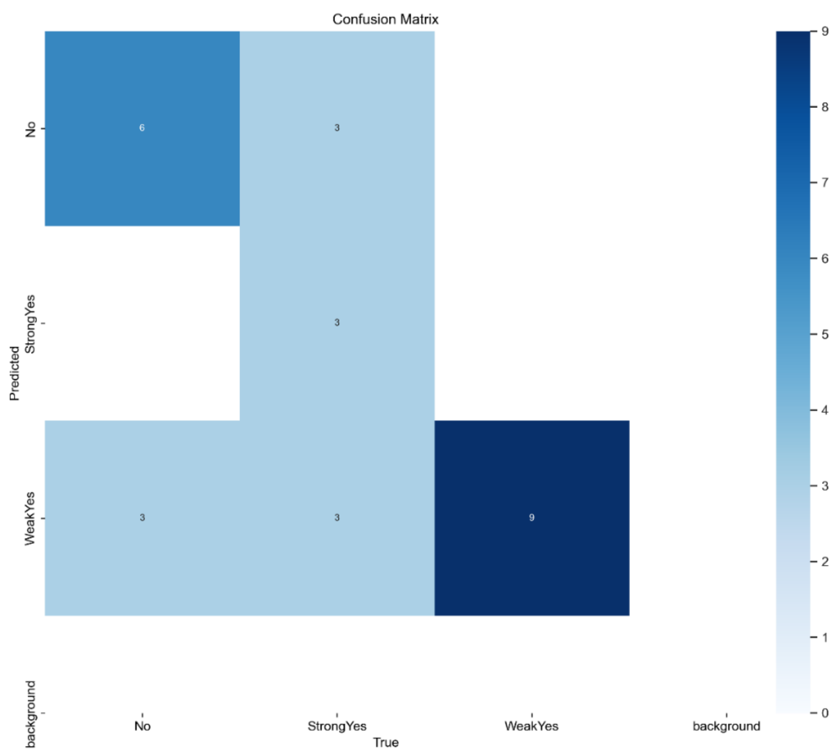


Figure 5. Confusion matrix for the movement classification model.



Finally, the ear detection model was trained for a total of 10 epochs, achieving an overall mAP of 0.983 at 0.5 IoU for both classes. The *Ears Erect* class revealed a mAP of 0.995 at 0.5 IoU, and the *Ears Neutral* class exhibited a mAP of 0.972 at 0.5 IoU. This model achieved acceptable performance for both mAP and IoU.

Discussion

Both the instance segmentation and ear detection models demonstrated acceptable performance in accordance with their mAP and IoU, serving as important building blocks for developing a more accurate movement classification model.

However, the classification model likely suffered from a combination of limited datasets (especially for the *Strong Yes* class) and difficulty in interpreting *Weak Yes* responses. As discussed previously, criteria for a *Weak Yes* response could include no movement with relaxed ears or any amount of movement paired with erect ears. Although the latter is uncommon, it was observed a few times in this dataset. Because this model prioritizes the amount of movement over other qualifiers, an animal with perfectly erect ears who lacks full lordosis may be assigned to the *No* class. Likewise, an animal with a fully locked back but with relaxed ear posture may be incorrectly classified as a *Strong Yes*.

Additionally, because *Strong Yes* responses were scarce, the 308 images trained and validated for this class were sourced from only three distinct applications of the BPT, whereas images from the *Weak Yes* and *No* classes were assembled from videos of six to ten individual animals, all on different days. A lack of subject diversity in one class (*Strong Yes*) may have contributed to the model's failure to appropriately recognize other animals.

Ultimately, of the nineteen healthy gilts who were able to receive transrectal ultrasounds and produce reliable physiological data, 42% displayed the expected positive BPT response in congruence with large follicular growth; 32% displayed the expected negative BPT response in congruence with minimal to no follicular development; and 26% displayed no signs of estrus despite growing large follicles, a phenomenon known as silent estrus. The latter occurrence likely contributed to the lack of *Strong Yes* examples on which to train the model.

Future iterations of this model may consider trialing shorter image intervals. While steps of five were used for this model, shorter intervals of two to four images may convey more accurate movement patterns.

Another important consideration for improving this model is exploring the possibility of audio. Because most animals in estrus will remain silent while mounted, an audio component paired with the existing model may assist in correctly assigning *Strong Yes* and *No* classes.

Conclusion

A YOLOv8 instance segmentation model detected the outline of gilts in single-stall housing with an overall mean average precision (mAP) of 99.5% at 0.5 intersection over union (IoU). Therefore, the result was adequate for automatic instance segmentation of individually housed pigs. A YOLOv8 movement classification model assigning three classes of behavioral responses to gilts receiving the back-pressure test (BPT) showed high false positive rates for one class and high false negative rates for two classes. This model is not yet satisfactory in automatically classifying types of behavioral responses to the BPT. A YOLOv8 object detection model for distinguishing erect ear posture from neutral ear posture had a mAP of 98.3% at 0.5

IoU for all classes, which is satisfactory for automatic detection of ear posture in gilts. Future directions for this study include adding additional images of the *Strong Yes* response to the dataset and sourcing the images from multiple animals. Additionally, the model may be improved by incorporating an audio component. While our data does reflect that gilts in estrus display less general movement during the BPT, our segmentation and movement classification models of BPT images do not yet demonstrate the ability to accurately assess whether an animal is in estrus based on their reaction to the BPT. If the model can be improved to a higher positive predictive value (PPV) for both *Strong Yes* and *No* responses, it may eventually be useful in aiding farm laborers' assessments of the BPT.

CHAPTER 3: A COMPUTER VISION MODEL FOR AUTOMATIC POSTURE IDENTIFICATION OF PREPUBERTAL GILTS

Abstract

Most pigs in the modern commercial swine industry are bred by artificial insemination. Appropriately timing ovulation is difficult, so producers typically rely on the back-pressure test to assess estrus, estimate ovulation, and determine the best time for insemination. However, conducting the back-pressure test is time-consuming and requires specialized knowledge. Producers assessing estrus in prepubertal gilts can reduce their dependency on specialized labor with the incorporation of computer vision technology that automatically detects postural changes. This thesis research aimed to 1) create a 24-hour dataset of images capturing behaviors of first estrus gilts from estrus through metestrus, 2) create an object detection model using YOLO (You Only Look Once) to detect postures in gilts, and 3) run the object detection model on the 24-hour dataset to assess whether postural changes are correlated with various stages of the estrous cycle. Digital images of gilts from pre-puberty through completion of first estrus were labeled for four postures (kneeling, sitting, lying and standing). A model was then trained on the images using YOLOv8 architecture, achieving an overall average 0.976 mean average precision (mAP) at 0.5 intersection over union (IOU). The resulting model was applied to a 24-hour dataset containing images of five additional gilts from 2 days pre-estrus synchronization through day 8. This model was used to create time budgets for each animal according to the four postures detected. No statistically significant differences existed among the four postures between pre-puberty and the conclusion of estrus.

Introduction

A longtime problem impacting the swine industry has been its reliance on specialized labor, particularly in the estrus detection process. Because artificial insemination (AI) is the reproductive means for over 90% of pigs worldwide, accurate and appropriate timing of estrus is more important than ever (Waberski et al., 2019). The estrus phase of the estrous cycle is punctuated by the maturation of antral follicles and subsequent ovulation, the latter of which typically occurs within 24 - 48 hours of estrus onset (Hines, 2023). To increase the chances of successful insemination, producers must strive to detect estrus - thus inferring the window of ovulation - as early and accurately as possible (Lammers et al., 2017).

For several decades, the standard method for estrus detection in pigs has been the back-pressure test (BPT), an assessment that requires an animal handler to push and rub the flanks of a female in the presence of a physical boar or augmented boar stimuli to assess her reaction (Langendijk, 2001). This reaction is a physical indicator of sexual receptivity. Should a female exhibit a strong standing response (typically indicated by a stiff, frozen posture with an arched back and erect ears), the handler can infer that the female is in estrus and likely within 48 hours of ovulation. This physical cue would then prompt the producer to inseminate the female within the presumed ovulation window. As the industry has shifted away from natural mating services in the last three decades, accurate estrus detection has become imperative in the timing of artificial insemination and in maximizing the labor and financial resources invested into the process.

However, despite the industry's reliance on the back-pressure test dating back to the 1970s (Reed, 1969 and Signoret et al., 1975), there is minimal data reporting its true accuracy, and appropriate alternatives have yet to see widespread adoption in the commercial industry. Beyond its unknown accuracy, the back-pressure test is subject to additional problems such as the requirement for specialized labor to conduct and evaluate the assessment; the physical labor involved in handling an animal that weighs over 135 kg; and the lack of standardized metrics with which to evaluate the female's response, leading to subjective assessments that may fluctuate based on the handler conducting the assessment.

Because responses to the back-pressure test can be ambiguous regardless of the animal's development of mature follicles (a problem known as silent estrus), and in combination with the BPT's variable accuracy, producers tend to practice double - or even triple - insemination. Doubling the number of insemination doses increases the chances that a female will become pregnant (Lamberson et al., 2000). An animal of reproductive age who does not get pregnant is an unproductive animal. Therefore, producers are forced to choose between spending extra money on additional inseminations in the hope that one will stick, or gambling on a single insemination dose, thus accepting the risk of feeding and housing an unproductive animal until her next cycle should she not become pregnant.

Currently, few viable alternatives to the BPT have seen widespread implementation in the swine industry. A new system for detecting estrus would need to: (1) demonstrate clear and consistent accuracy when compared to the BPT, (2) operate without the need for highly specialized labor, (3) properly identify and detect ambiguous postures and behaviors, and (4) demonstrate broad application. Our hypothesis is that gilts in estrus will display more active behaviors than resting behaviors during estrus when compared to metestrus. Additionally, we hypothesize that an object detection model can be used to identify these behavioral and postural changes, which may eventually be used for estrus detection.

This thesis sheds light on the need for alternatives to the back-pressure test that are standardized, cost effective, and easy to use. We suggest a computer vision approach that, with some alterations, may successfully address these criteria.

Materials and Methods

Animal and Housing Specifics

This study was conducted at the Swine Research Center at the University of Illinois in Champaign, Illinois. Images were collected from six populations of Yorkshire x Landrace gilts at six separate time points between April 2022 and May 2023. All gilts were prepubertal and age-matched within each replicate. The ages of the six replicates ranged from 168 to 185 days. Animals were housed in the same room, in single-stall confinement. Stalls were arranged in four clusters of three stalls each. The initial five replicates from April 2022 through September 2022 were managed with lights on during daylight hours. Barn doors remained closed, but inside temperature was mediated by internal fans. Gilts were moved from finishing barn pens to single stall confinement within 24 hours of the first study treatment. The sixth replicate, in May 2023, moved gilts from finishing barn pens to single stall confinement 72 hours prior to the start of the initial study treatment. For ease of detecting images and scoring animal behavior, lights were left on 24/7 throughout the duration of this replicate. Temperatures ranged from a low of 52º on the morning of May 10 to a high of 82º on the afternoon of May 14. Across all ten days, mean temperature was 67º and mean humidity was 49.3%. Animals across all six replicates were fed once daily with *ad libitum* access to water.

Replicate one collected images of five gilts over a period of five days. Replicates two and three collected images of six gilts each over six and seven days, respectively. Replicates four and five collected images of twelve gilts each over six days. Finally, replicate six collected images of twelve gilts over ten days. The first five replicates were recorded and observed once per day during the administration of the back-pressure test only. The final replicate was recorded continuously for ten days.

Data Collection

To capture image data, a Microsoft Kinect V2 camera was centered and installed above each cluster of three stalls. Digital color images were taken at one-second intervals and stored on external hard drives. They were later converted using an image processing program developed with MATLAB software.

Fifty percent of the animals in replicates one through four were injected with PG600 on day 0 to synchronize estrus (treatment was administered to two of the five gilts in replicate one). Due to a low number of positive estrus responses observed in the initial four replicates, all twelve gilts in replicate five were injected with P600 on day 0 with the goal of maximizing positive behavioral responses. Each gilt in the initial five replicates was exposed to once daily fence line boar contact, and the back-pressure test was administered to each gilt during this time.

In the sixth and final replicate, all twelve gilts were injected with PG600. All animals had once daily fence line boar contact, but the back-pressure test was only administered to six of the twelve gilts. The remaining six gilts were visually observed for signs of estrus but were not physically handled by the researchers during this time.

All six replicates relied on transrectal ultrasounds to assess antral follicular growth. Ultrasounds were performed on day 0 and day 4 of each replicate to establish baseline measurements. Animals that did not exhibit healthy, 2 – 4 mm follicles on the initial ultrasound were excluded from the treatment group and did not receive PG600. Ultrasounds were again conducted on day 4 to measure follicular growth and confirm ovulation. Animals that subsequently developed cystic ovaries or other ovarian abnormalities were excluded from the analysis.

Information on each gilt's response to the back-pressure test was recorded on a paper log. Each replicate was followed until each gilt within the replicate demonstrated a negative response to the back-pressure test following earlier expression of estrus, indicating a return to metestrus. Therefore, some replicates were followed for a longer period to allow all animals to return to baseline behavior.

Data Analysis

Animals were divided into two datasets. Top-view images from forty-one gilts (obtained from replicates one through five) were labeled using the open-source data labeling platform LabelStudio. The four postures chosen for labeling were kneeling, sitting, standing, and lying (Table 2). Bounding boxes were drawn around each animal, and a posture was assigned to each box (Figure 6). In total, 1,361 images were labeled, amounting to 553 instances of kneeling; 929 instances of sitting; 1,510 instances of standing; and 1,143 instances of lying. Labels and images were exported in YOLO format to facilitate model development. This dataset was then used to train an Ultralytics YOLOv8 object detection model. 80% of images were reserved for training the model and the remaining 20% were used for validation. The posture model was ultimately trained for 30 epochs.

Table 2. Ethogram of gilt postures, for use in image labeling

Posture	Description
Kneeling	Rear is raised and front legs are bent
Lying	Laying sternally or laterally with stomach touching the ground
Sitting	Rear is on ground with front legs upright
Standing	Upright with all four legs extended

Figure 6. Example of postures labeled with bounding boxes for use in an image detection model. From left to right: lying, kneeling, and standing.

The second dataset was created by running the posture detection model on 1,420,815 images of five gilts taken from replicate six. These five gilts were selected due to their predictable ovulation dates, which were inferred from a combination of ultrasound data and behavioral cues. The remaining seven gilts from replicate six were excluded due to a combination of development of cystic ovaries and ambiguous ovulation dates.

Mean average precision (mAP, equation 11) and intersection over union (IoU, equation 12) were reported for each model. Additionally, calculations were conducted for positive predictive value (PPV, equation 13); negative predictive value (NPV, equation 14); sensitivity (equation 15); specificity (equation 16); precision (equation 17); recall (equation 18); accuracy (equation 19); and error (equation 20).

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i(2) \quad [11]$$

where

mAP = mean average precision

AP = average precision

N = number of classes

$$IoU = \frac{|A \cap B|}{|A \cup B|}(1) \quad [12]$$

where

IoU = intersection over union

A = area of label box

B = area of predicted box

$$PPV = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad [13]$$

$$NPV = \frac{True\ Negative}{True\ Negative + False\ Negative} \quad [14]$$

$$Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad [15]$$

$$Specificity = \frac{True\ Negative}{True\ Negative + False\ Positive} \quad [16]$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad [17]$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad [18]$$

$$Accuracy = \frac{True\ Positive + True\ Negative}{True\ Negative + False\ Positive + True\ Positive + False\ Negative} \quad [19]$$

$$Error = \frac{False\ Negative + False\ Positive}{True\ Negative + False\ Positive + True\ Positive + False\ Negative} \quad [20]$$

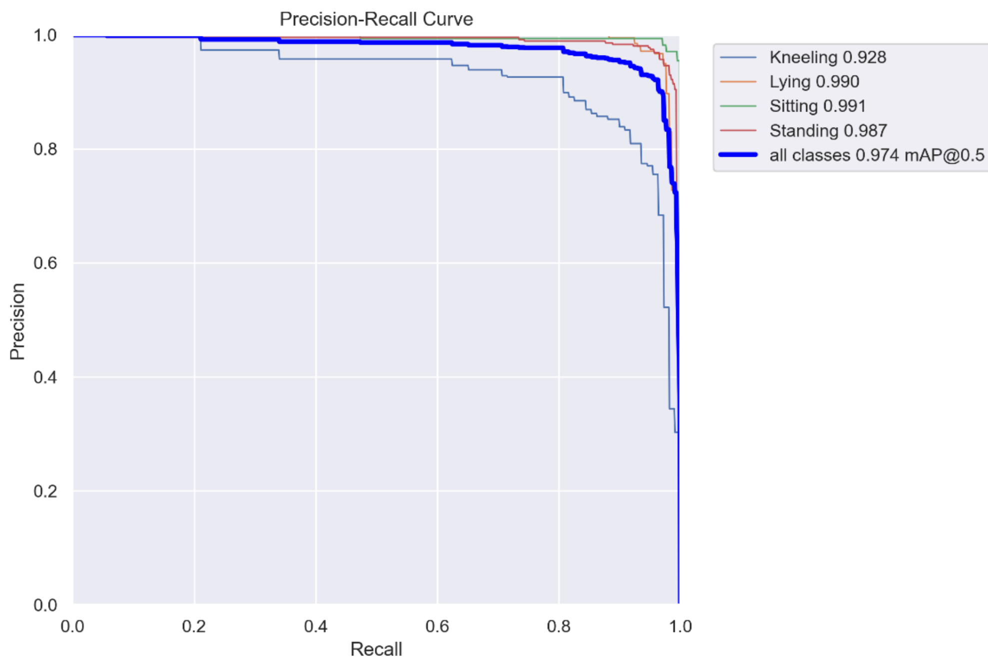
The goal of assembling this dataset was to create a 24-hour time budget comparing postural changes over the course of ten days, from pre-puberty through estrus and into metestrus.

Results and Discussion

Model Training

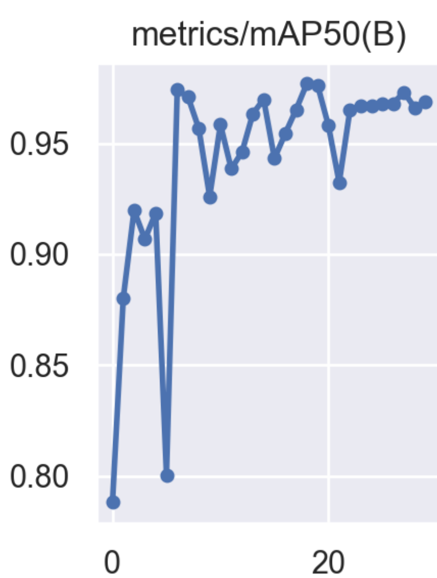
Mean average precision (mAP) indicates a model's accuracy in predicting class names, and intersection over union (IoU) reflects a model's ability to correctly predict the location of bounding boxes. A desirable metric for both mAP and IoU is close to 1.0. After training the model for 30 epochs, it achieved a mean average precision of 97.60% for all classes at 0.5 IoU and 86.69% at 0.5 – 0.95 IoU for all classes. The precision-recall curve and mean average precision at both 0.5 and 0.5 – 0.95 IoU for all classes are shown in Figure 7.

Figure 7. Precision-recall curve (a), mAP 0.5 (b), and mAP 0.5-0.95 (c) for all postures over 30 epochs. Precision is a measure of quality and reflects the size and fit of each predicted bounding box or mask. Recall is a measure of quantity and reflects the number of boxes or masks predicted as a proportion of the total number of animals or objects that exist in the image. Balance is desired between the two metrics; thus, an optimal perfect precision-recall is close to 1.0.



a

.



b **c**

Metrics were calculated for each posture using a confusion matrix generated from the validation set. Positive predictive values (PPV) for kneeling, sitting, standing, and lying were 0.71, 0.99, 0.92, and 0.97, respectively. Negative predictive values (NPV) for the four postures were 0.99, 0.98, 0.96, and 0.90. The kneeling posture had an accuracy of 92% with an error rate of 8.0%. It achieved a sensitivity and recall of 0.96, a specificity of 0.91, and a precision of 0.71. The sitting posture had an accuracy of 98.5% with an error rate of 1.5%. It had a sensitivity and recall of 0.95, a specificity of 0.996, and a precision of 0.99. The standing posture achieved an accuracy of 95.2% with a 4.8% error rate, alongside a sensitivity and recall of 0.89; specificity of 0.97; and precision of 0.92. Lastly, the lying posture demonstrated a 92.1% accuracy with an error rate of 7.8%. Its specificity and recall were 0.985; precision 0.97; and recall 0.81. These values are reflected in Table 3.

Table 3. Performance metrics of the posture detection model

	Strong Yes	**Weak Yes**	**No**
PPV	**1.0**	**0.6**	**0.67**
NPV	**0.75**	**1.0**	**0.83**
Accuracy	**0.77**	**0.77**	**0.77**
Error	**0.22**	**0.22**	**0.22**
Precision	**1.0**	**0.6**	**0.66**
Recall	**0.33**	**1.0**	**0.66**
Specificity	**1.0**	**0.66**	**0.83**

Posture Prediction

The trained YOLOv8 model was used to predict postures for the five gilts in replicate six with predictable ovulation days. Data was used from five of the ten total days of observation (day -2 through day 2, with ovulation as day 0). Table 4 depicts the amount of time spent daily in each posture by each gilt. On average across the five gilts, the animals spent approximately 19 hours and 14 minutes per day total in the lying position (80.16%); 2 hours and 22 minutes in the standing position (9.9%); 1 hour and 48 minutes in the sitting position (7.51%); and 13 minutes in the kneeling position (0.89%). Averages across all gilts are reflected in Figure 8.

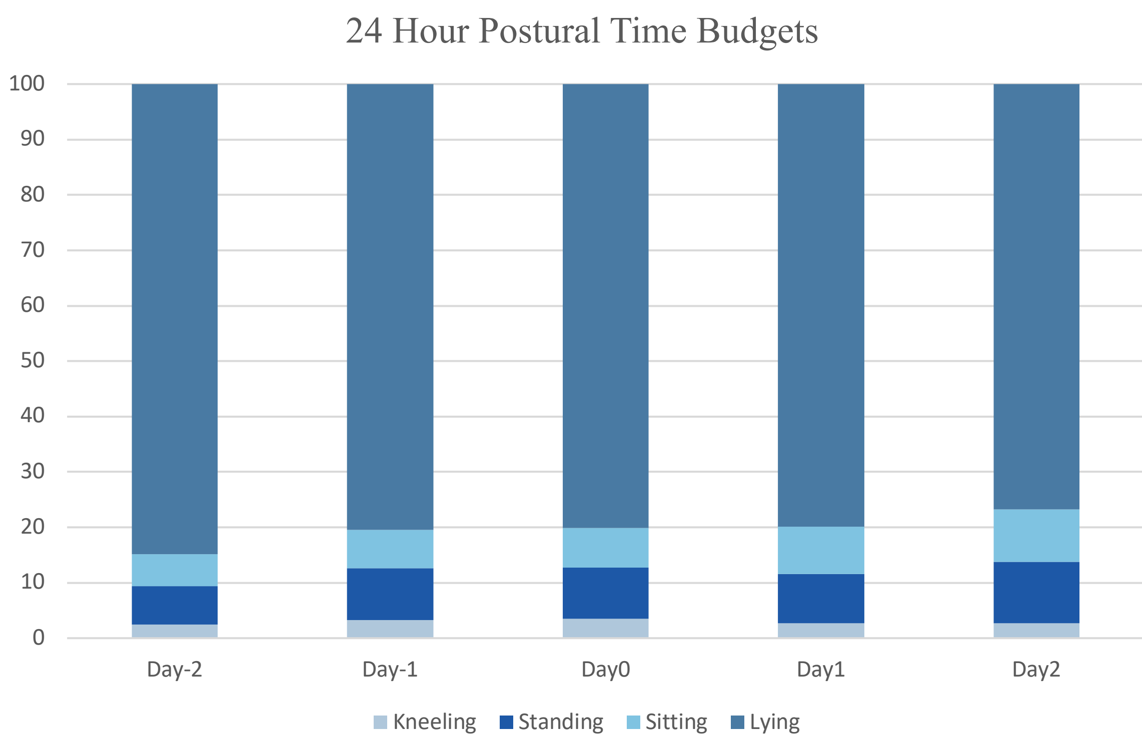
Table 4. Percentage of time spent in each posture per 24 hours, organized by gilt.

Pig ID	Day	Kneeling	Standing	Sitting	Lying
13	-2	0.60	4.00	10.70	84.70
13	-1	0.60	4.90	11.50	82.90
13	0	0.50	3.90	11.30	84.30
13	1	0.70	6.50	10.20	82.50
13	2	1.30	11.80	13.70	73.20
14	-2	0.20	2.60	2.60	94.60
14	-1	0.30	10.40	6.60	82.70
14	0	0.10	8.50	9.00	82.40
14	1	0.10	13.10	10.60	76.00
14	2	0.15	9.10	7.90	82.90
22	-2	9.80	9.80	6.20	72.80
22	-1	12.50	12.50	8.60	65.40
22	0	14.30	14.30	6.50	65.50
22	1	10.10	10.10	9.50	63.30

Table 4. (cont)

22	2	9.20	9.20	11.50	62.40
23	-2	0.65	16.60	4.60	78.00
23	-1	0.65	16.20	4.20	78.90
23	0	0.50	17.40	4.40	77.70
23	1	0.30	12.90	7.20	79.50
23	2	0.30	22.50	10.50	66.50
24	-2	1.30	1.30	5.00	86.60
24	-2	2.50	2.50	3.80	87.50
24	0	2.00	2.00	4.70	87.00
24	1	2.00	2.00	5.50	81.50
24	2	2.70	2.70	3.50	86.10

Figure 8. Graph representing the average amount of time spent in each posture.



The amount of time spent in each posture and during each phase of the estrous cycle was highly variable. A repeated-measures ANOVA was performed for each of the four postures using SPSS statistics software. Because the assumption of sphericity was not met, a Geisser-Greenhouse correction was applied to the data. p-values for kneeling, sitting, standing, and lying were 0.437, 0.090, 0.296, and 0.088, respectively (Table 5). Therefore, results of the ANOVA indicated no statistical differences in time spent in each posture before, during, or after ovulation.

Table 5. Analysis of variance results, with Greenhouse-Geisser correction applied.

Posture	Sum Sq.	d.f.	Mean Sq.	F	Sig.
Kneeling	4.397	1.599	2.751	0.852	0.437
Sitting	40.462	2.520	16.055	2.953	0.090
Standing	44.710	2.038	21.940	1.422	0.296
Lying	235.576	1.544	152.600	3.850	0.088

Discussion

Ultimately, of the nineteen healthy gilts who were able to receive transrectal ultrasounds and produce reliable physiological data, 42% displayed the expected positive BPT response in congruence with large follicular growth; 32% displayed the expected negative BPT response in congruence with minimal to no follicular development; and 26% displayed no signs of estrus despite growing large follicles, a phenomenon known as silent estrus. The latter is a pervasive concern with prepubertal gilts, and the ability to visually detect estrus in this group was an objective of this thesis that has not yet been fulfilled by the aforementioned machine learning models.

Because the 24-hour dataset was not manually annotated but rather validated using a posture detection model with 97% accuracy, the resulting postures can only be considered tendencies, as opposed to definite representations of actual postures. The most frequently misidentified posture was kneeling (confusion matrix shown in Figure 9). Additionally, lateral lying was occasionally misinterpreted as standing when the animal's legs were fully extended. This was largely an oversight in the initial model training process, as nearly all labeled lying postures were in the sternal position. Future iterations of the model could be improved by exposing the model to more side-lying postures during training. Ideally, an equal number of lateral left and lateral right postures would assist in further balancing the dataset.

A surprising result was the total amount of time spent in the dog-sitting position. Dog-sitting is a stereotypic behavior often associated with stress and sub-optimal welfare (Cagienard et al., 2005). Increasing occurrences of dog-sitting have been correlated with poor welfare conditions, of which boredom could be a factor (Vitali et al., 2021). Morita et al. (1998) found that pigs kept in narrow confinement with minimal enrichment were more likely to change position, including dog-sitting. This is reinforced by the finding that fattening pigs maintained in a free-range forest enclosure spent only 1.3% of their time on average in the sitting position. The average duration of a sitting event lasted between 10 and 90 seconds (Stabler et al., 2022). The amount of sitting time detected in this thesis research is comparatively considered abnormal. Explanations for this stereotypic behavior could include confinement in individual stalls with no enrichment; stress and discomfort from transrectal ultrasounds; and lack of a proper acclimation period. Gilts in this study were moved from group finishing barns to individual stalls only 24 – 48 hours prior to the start of observation; future iterations of this research should consider a full acclimation period of 10 – 14 days prior to treatment and observation.

Figure 9. Confusion matrix for model of posture detection.

Conclusion

A YOLOv8 object detection model detected four postures (kneeling, sitting, lying, and standing) in prepubertal gilts with an overall mean average precision (mAP) of 97.60% at 0.5 intersections over union (IoU). The mAP for all four classes was above 94.80% at 0.5 IoU. Therefore, these results are adequate for automatic behavior analysis. There were no statistically significant differences between stage of estrus and amount of time spent in any one posture. Future directions for this study would include analyzing more instances of lateral recumbency to improve the model's distinction between lying and standing. Additionally, the model may benefit from analysis of depth images in addition to color images, which would likely contribute to an increased mAP for kneeling and lying postures. Currently, the model is 97.6% accurate in detecting four postures in prepubertal gilts, allowing us to confirm our hypothesis that an object detection model can be used to identify postural changes in gilts. If future iterations of the model can improve the accuracy of lying, standing, and kneeling postures and the model is tested on a larger dataset of gilts with known ovulation dates, there may be greater accuracy in determining whether postural changes exist between stages of the estrous cycle. If the latter is determined to be true, this model may eventually be useful in the detection of first estrus in prepubertal gilts.

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