3D DEPTH IMAGING FOR PIG WEIGHT ESTIMATION

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Livestock weight estimation is a fundamental aspect of animal husbandry, directly influencing decisions regarding feeding schedules, growth monitoring, health management, and market readiness (Wang et al., 2024). Among various livestock species, pigs are a primary focus due to their significant contribution to global meat production. Pigs account for approximately 36 percent of the world's meat consumption, surpassing other livestock such as cattle and poultry, making them an economically critical species (Food and Agriculture Organization (FAO), 2022). Accurate weight estimation in pigs ensures optimal feed conversion rates, reduced production costs, and improved animal welfare, which are essential for sustainable farming practices (Terence et al., 2024).

In traditional farming methods, weighing scales are the standard tool for livestock weight measurement. However, these methods are often labor-intensive, time-consuming, and stressful for animals, potentially leading to injuries and a decline in productivity (Faucitano and Goumon, 2018). For smaller farms, the high costs and maintenance requirements of weighing systems make them less feasible. To address these challenges, farmers and researchers have explored alternative methods, such as using a measuring tape or string to estimate pig weight based on body measurements like heart girth and length (The Pig Site, nd). While these methods are cost-effective and less stressful, they are prone to inaccuracies due to human error and inconsistent measurement techniques.

Advancements in technology, particularly computer vision (CV) and machine learning (ML), have introduced more efficient and precise methods for weight estimation. Depth-sensing devices like Microsoft Kinect offer a non-invasive and cost-effective solution by capturing 3D data to estimate body weight with high accuracy (Pezzuolo et al., 2018). Compared to manual measurement methods or even traditional scales, these technologies significantly reduce labor, improve accuracy, and minimize stress on animals. Moreover, the integration of 3D imaging and ML algorithms enables the creation of automated systems that adapt to diverse farm environments, making them ideal for small and medium-sized farms (Gjergji et al., 2020).

Manual methods such as using measuring tapes involve wrapping a tape or string around the pig's heart girth and measuring its body length, followed by applying a formula to estimate weight (The Pig Site, nd). While accessible and inexpensive, this method is laborious and lacks precision, especially when dealing with active or uncooperative animals. Traditional weighing scales, though accurate, require direct handling of pigs, posing risks to animal welfare and farmworkers (Dickinson et al., 2013). In contrast, advanced systems leveraging depth-sensing technology provide non-invasive and automated solutions. For instance, Kinect sensors capture detailed 3D images, enabling precise calculations of body volume and weight without requiring physical contact with the animal (Pezzuolo et al., 2018). These systems mitigate stress, enhance accuracy, and save labor, making them a promising alternative to traditional methods. However, the initial cost and need for technical expertise can pose barriers to adoption, especially for resource-constrained farms.

Accurately estimating pig weight is critical for achieving optimal feed-to-weight conversion ratios, a key determinant of farm profitability. Weight monitoring also supports health assessments, helping detect early signs of disease or malnutrition, which can otherwise lead to significant economic losses. Furthermore, precise weight data allows farmers to determine the ideal market timing, maximizing revenue and ensuring meat quality standards are met (Terence et al., 2024).

This study aims to develop a system for pig weight estimation by leveraging Kinect V1's depth-sensing capabilities. The proposed system seeks to reduce labor, improve measurement precision, and enhance animal welfare. This research contributes to the broader adoption of sustainable, efficient farming practices by addressing the practical challenges of traditional and manual weight estimation methods. The findings may pave the way for integrating advanced depth-sensing technologies into modern livestock management systems, supporting the transition toward precision agriculture and smart farming practices.

1.2 Statement of the Problem

Accurate weight estimation is a cornerstone of efficient pig farming, influencing critical decisions such as feed management, health monitoring, growth tracking, and market readiness. Traditional weighing methods, which involve manually moving pigs to weighing scales, are not only labor-intensive and time-consuming but also stressful for the animals. This stress can adversely affect the pigs' well-being, reducing their productivity and potentially impacting meat quality (Li et al., 2014). The labor-intensive nature of manual weighing also increases operational costs, posing a challenge for farmers, particularly in small- to medium-scale farms where resources are limited.

To circumvent these challenges, farmers often resort to alternative methods, such as using a measuring tape or string to estimate pig weight. This method involves measuring dimensions like heart girth and body length, then applying a weight estimation formula (The Pig Site, nd). While this approach is cost-effective and non-invasive, it is prone to significant inaccuracies due to human error, variability in measurement techniques, and difficulty in handling active or uncooperative animals. These inaccuracies can lead to suboptimal feeding strategies, delayed health interventions, and missed opportunities for maximizing market profitability.

In recent years, advancements in imaging technologies have paved the way for automated, non-invasive weight estimation methods. Single-camera systems and monocular vision techniques, while offering some improvements, often fail to capture precise depth information, which is crucial for accurate volume and weight estimation (Pezzuolo et al., 2018); (Kollis et al., 2007). These systems are further limited by environmental factors such as lighting variations and animal movement, which compromise their reliability and usability in real-world farm settings.

Multi-camera setups have emerged as a more accurate alternative, enabling the capture of detailed 3D data necessary for precise weight calculations (Dohmen et al., 2022). However, these setups are often prohibitively expensive and complex, requiring specialized equipment, significant computational resources, and skilled personnel to operate. This makes them inaccessible to many farmers, especially those in resource-constrained environments. Additionally, while machine learning algorithms and other modeling techniques have been applied to refine weight estimation processes, their effectiveness is limited by the quality of input data, which often suffers from incomplete 3D reconstructions or inconsistencies in 2D images.

A promising yet underexplored solution lies in utilizing Microsoft Kinect V1, a cost-effective and readily available depth-sensing camera originally developed for gaming applications. The Kinect V1 captures depth data by projecting an infrared (IR) pattern onto the surface of an object and analyzing the distortions to calculate depth values. This enables the generation of detailed 3D point clouds that can be used to accurately measure body volume and, subsequently, estimate weight (Zhang, 2012). Despite its potential, the Kinect V1 remains underutilized in the domain of livestock management, and existing research has not fully explored its capabilities for precise and non-invasive weight estimation.

This gap in the literature highlights the need for a practical and accessible system that leverages Kinect's depth-sensing technology for weight estimation in pigs. Unlike traditional methods or multi-camera systems, the Kinect V1 offers a simpler, more affordable solution capable of capturing high-quality depth data in real-time. By automating the weight estimation process, the Kinect V1 can significantly reduce labor requirements, minimize stress on animals, and improve the accuracy of measurements.

This research aims to bridge this gap by leveraging the depth-sensing capabilities of the Kinect V1 to develop a cost-effective and automated system for pig weight estimation. Unlike previous approaches that rely on more complex and expensive setups, the Kinect-based system provides detailed depth information for accurate body volume measurements. By addressing the challenges of traditional and existing imaging methods, this study seeks to create a solution that minimizes labor, reduces stress on animals, and enhances measurement precision. The findings from this research could revolutionize weight monitoring practices in pig farming, particularly for small and medium-scale farms, and contribute to the advancement of precision agriculture and smart farming techniques.

1.3 Objectives of the Study

The main objective of this study is to develop a non-invasive Pig Weight Estimation System that utilizes depth imaging, specifically:

1. To utilize machine learning algorithms for model training and validation to analyze depth data for pig weight estimation.

2. To develop a web application for the Pig Weight Estimation System.

3. To assess the accuracy of the Kinect-based pig weight estimation system.

1.4 Significance of the Study

The results of this study would benefit the following:

Academe. This study will contribute to the existing knowledge on the application of computer vision technology in the industry, particularly in livestock management. This study could serve as a valuable reference for academic institutions for agriculture, computer science, engineering, and computer vision technology. The findings of this study can also be an inspiration for further research in these fields of study.

Business Owners. This study can offer business owners, particularly those in the agricultural and livestock sectors a more efficient and data-driven method of managing their livestock operations. The results of this study can help automate tasks such as livestock monitoring, feed rationing, and health checks. This can reduce labor costs and improve decision-making processes. Additionally, this innovation can encourage entrepreneurship in tech-driven agriculture, creating business opportunities.

Livestock Caretakers. The results of this study can aid in the adoption of computer vision technology in livestock agriculture and can assist livestock caretakers in optimizing feed rations, monitoring growth rates, and improving overall herd management. Thus can ensure better animal health and welfare, reduce workload, and enhance productivity by providing data-driven insights into the daily operations of the livestock.

Government Organizations. Government organizations can utilize the study's findings to develop strategies that promote the modernization of agriculture through technological adoption. By using computer vision technologies, government organizations can improve farm-to-market systems and boost overall agricultural productivity.

Veterinarians. Results from this study could assist veterinarians involved in livestock by creating tools that enable veterinarians to remotely monitor, reducing the need for frequent on-site visits. It can also help in establishing preventive care strategies by being able to identify early signs of illness through variations in weight, improving animal welfare.

Agriculture Technology Developers. Companies and developers in the field of agricultural technology can use the findings of this study to design and enhance their products. The research can inform them about the specific needs of livestock management and provide insights into how computer vision solutions can be tailored to address these requirements, resulting in more market-relevant and effective innovations.

Future Researchers. This study can be used as a future reference for researchers who plan to engage in the same field of study. It can potentially be adapted for other agricultural applications, leading to increased efficiency and productivity in the sector. The methodologies found in the study can guide subsequent research, encouraging innovation and advancement in agriculture technology.

1.5 Scope and Limitations

This research will focus on the estimation of weight in Landrace pigs using the Kinect sensor under controlled conditions, including consistent height, posture, and lighting. Landrace pigs are commonly used in commercial pig farming in the Philippines due to their desirable traits such as high reproductive efficiency, good growth rates, and quality meat production (Mañez et al., 2020). The Landrace breed is particularly well-suited for the tropical climate of the Philippines due to its adaptability, disease resistance, and efficient feed conversion. These pigs typically reach a market weight of around 90-120 kg at 6-7 months of age and demonstrate a high average daily gain (ADG) of approximately 0.7–1.0 kg/day under optimal feeding conditions.

Optimal feeding conditions refer to a balanced diet that ensures the pigs' growth and health, which includes proper nutrition, adequate water intake, and appropriate feed quality. The diet typically consists of a mixture of high-protein grains such as corn, soybeans, and wheat, along with essential vitamins and minerals that promote muscle development, immune health, and overall well-being. The quality and quantity of the feed are adjusted to ensure that the pigs' energy and nutritional requirements are met, based on their age, weight, and stage of growth. Additionally, it is important to provide sufficient clean water, as water intake is directly linked to feed consumption, digestion, and growth performance.

In optimal feeding conditions, pigs are typically fed in multiple phases, with adjustments made as they grow. For example, piglets may be given a starter feed high in protein and energy, while finishing pigs (those close to market weight) may receive a grower or finisher diet designed to maximize weight gain while maintaining feed efficiency. Regular monitoring of the pigs' health and growth patterns is also essential to ensure that the feed provided aligns with the pigs' developmental needs. Feeding strategies also take into account environmental factors such as temperature and humidity, which affect the pigs' metabolism and feed conversion efficiency. Under these optimal conditions, Landrace pigs are expected to gain weight at an average daily rate of 0.7–1.0 kg/day, making them one of the most productive pig breeds in terms of growth.

Given these factors, Landrace pigs are the primary focus of this study, as their standardized growth patterns allow for more accurate and consistent data collection. Other pig breeds with different body shapes or growth rates may present variables that are outside the scope of this study, which is why the results will be limited to Landrace pigs.

The study will specifically analyze data from pigs in a straight posture, as posture can significantly affect the accuracy of Kinect's depth-sensing capabilities. Pigs in non-straight postures or with significant variation in body alignment will be excluded to maintain the integrity of the measurements. Variations in posture could cause inconsistencies in the depth image capture, potentially leading to inaccurate weight estimates. Therefore, a consistent and controlled posture will be required for all subjects.

Environmental conditions, such as lighting and background, will be standardized to minimize their impact on sensor accuracy. However, the influence of environmental factors on Kinect sensor performance will not be the primary focus of the study, as these conditions will be controlled to ensure optimal data quality. Future research could explore the sensor's performance in variable lighting or more complex backgrounds, but this will not be addressed in the present study.

The batch processing of collected data will be used primarily to train machine learning models that will enable real-time weight estimation in pigs.

The collected depth images, after being processed, will be analyzed to build models capable of estimating pig weight based on 3D body volume measurements. While the focus will initially be on post-processing, the resulting models will be designed to perform real-time estimation when integrated into a dynamic farm environment. This approach represents a key step in the development of a practical, non-invasive weight estimation system that could be used in active pig farming operations once the system is fully trained.

1.6 Definition of Terms

Artificial Intelligence - A set of technologies that enable computers to perform a variety of advanced functions, including the ability to see, understand, and translate spoken and written language, analyze data, make recommendations, and more.

Computer Vision A field of computer science that focuses on enabling computers to identify and understand objects and people in images and videos.

Deep Learning A subset of machine learning that uses multilayered neural networks, called deep neural networks, to simulate the complex decision-making power of the human brain.

Depth Imaging A technique that captures the distance between a sensor (like a depth camera) and objects in its view, creating a 3D representation of the scene. Depth imaging provides additional data on the spatial positioning of objects.

Landrace A domesticated, locally adapted, traditional variety grown by farmers and their successors since ancient times.

Image Processing Techniques used to enhance or extract information from images, are crucial for analyzing data from the Kinect sensor.

Machine Learning A subset of artificial intelligence that involves the use of algorithms to learn from data and make predictions or decisions based on that data.

Microsoft Kinect Sensor A motion-sensing input device that uses a camera to capture depth data and track movements.

Pig Weight Estimation The process of determining the weight of pigs uses various methods, in this case, image processing and machine learning.

CHAPTER 2

REVIEW OF RELATED LITERATURE

This literature review explores current weight estimation techniques in livestock management, highlighting the advancements and limitations of traditional methods while introducing emerging technologies, particularly depth-sensing devices like the Kinect sensor. Understanding the shift from conventional approaches to tech-driven solutions provides insight into how these innovations can improve accuracy, efficiency, and scalability in livestock farming.

2.1 Weight Estimation Techniques

In animal production, livestock body weight is a significant and widely used feature that has an impact on feed consumption, breeding potential, social behavior, energy balance, and overall farm management (Wang et al., 2024). It may be used indirectly in the assessment of health and welfare status (Dikmen et al., 2012). There are two main approaches to measuring body weight in livestock: (1) direct approaches using scales, and (2) indirect approaches based on relationships between body part measurement and body weight.

Direct weighing methods rely on weighing technologies such as partial-weight or full-weight industrial scales capable of supporting small, medium, or large livestock. Some companies provide passive-weighing solutions that integrate sensor-rich scaling systems such as GrowSafe of Canada, the Bosch Precision Livestock Platform of Germany, and Rice Lake Weighing Systems of Australia which are capable to measure, log results, and transmitting information over wired or wireless networks (Wang et al., 2024) . Other companies such as Arvet CIMA Control Pig and CIMA Control Cow Scaling Systems of Spain developed custom-made scales that provide dynamic-weighing systems where animals are weighed while in motion using walk-through or step-over weighers (Rousing et al., 2004). While these devices are very accurate, their acquisition, intended purpose and operation size, repeated calibration and maintenance costs associated with their placement in high-temperature variability, and corrosive environments are significant and beyond the affordability and sustainability limits of small and medium size farms and even commercial operators(Dikmen et al., 2012). It has been studied that removing animals from paddocks and holding areas and leading them to weighing stations is costly, stressful, and potentially harmful activity for animals and handlers alike and also inadvertently leads to animal weight loss or even death (Faucitano and Goumon, 2018). Moreover, since the weighing process is very laborious, the frequency of measurements is not sufficiently high to permit the use of body weight as an indicator for other traits. However, since the affordability of direct weighing methods may impede small producers (Dickinson et al., 2013), researchers have developed indirect weighing methods represented by regression models that relate morphometric measurements and image features to body weight in livestock. The direct acquisition of morphometric measurements can be accomplished with the aid of technologies with various degrees of complexity, from measuring tapes and types to specialized software or manual, semi-automatic, or automatic measurements extrapolated from images obtained with electro-optical devices such as mono-2D, stereo-2D, 3D, ultrasound, and infrared sensors (Wang et al., 2024).

2.1.1 Role of Technology in Agriculture

Technological advancements have played a pivotal role in transforming the agricultural sector. From mechanization to digital innovations, these technologies have increased efficiency, productivity, and sustainability in farming practices. In particular, precision agriculture, which uses technology to optimize field-level management of crop farming, has revolutionized the way food is produced (Witten et al., 1993). Precision farming technologies include GPS, soil sensors, and drones, allowing farmers to monitor and manage their crops with unprecedented accuracy. In livestock farming, technology has led to the development of automated feeding systems, health monitoring tools, and weight estimation systems that reduce labor and enhance animal welfare (Gómez et al., 2021). For example, sensor-based systems for monitoring livestock health provide farmers with real-time data, enabling proactive interventions to prevent diseases and improve overall herd management (Neethirajan and Kemp, 2021).

Furthermore, AI and machine learning have started to play an increasingly significant role in agriculture. These technologies enable predictive analytics for crop yields and disease outbreaks, and more recently, they are being used in 3D object detection systems for animal weight estimation, such as the Kinect-based system for pig weight estimation proposed in this study (**?**). Integrating AI and machine learning into agricultural practices is expected to address many challenges related to food security, sustainability, and labor shortages (Ng et al., 2023).

For example, one study explored the use of 3D images captured from a zenithal viewpoint to estimate lambs' live weight. The researchers applied image processing techniques to extract features such as upper body area and average depth, demonstrating the potential of 3D imaging for livestock weight estimation (Samperio et al., 2021). Although this study did not use Kinect, it highlights the value of 3D data, which Kinect is well-equipped to provide, for accurate livestock weight estimation.

Another significant study used the Microsoft Kinect V1 depth camera to measure pig body dimensions and estimate their weight. The researchers found a strong correlation between the Kinect-based measurements and actual weights, with coefficients of determination (R^2) exceeding 0.90 (Pezzuolo et al., 2018). Similarly, Lao et al. also employed a Kinect V1 depth camera to extract body measurements from pigs, developing a regression model for weight estimation, while Liu et al. used a binocular vision system to collect 3D data and tested various modeling approaches, including linear, nonlinear, and machine learning algorithms, to estimate pig weight (Li et al., 2014).

2.2 Technological Frameworks

The manual techniques used in the majority of livestock weight estimation systems today have given way to more automated, technologically advanced systems. Physical weighing scales, which were labor-intensive, time-consuming, and frequently uncomfortable for animals, were the foundation of traditional methods. On the other hand, cutting-edge image technologies are now used in modern systems, including 3D depth sensors like the Microsoft Kinect and binocular and monocular vision systems. For extremely precise

3D reconstructions of animals, binocular vision systems employ two cameras to collect stereo images; however, the expense and complexity of these installations may make them impractical for small farms (Rousing et al., 2004). Compared to binocular vision systems, monocular vision systems, which use single-camera setups, are more affordable but have worse precision.

Smart sensors are at the vanguard of revolutionizing precision agriculture by giving farmers access to real-time information on vital parameters including plant health, temperature, humidity, and soil moisture. With their sophisticated detection methods, these sensors assist farmers in making well-informed decisions that increase crop output. Farmers may automate and optimize tasks like nutrient application and irrigation scheduling by combining these sensors with Internet of Things (IoT) devices and artificial intelligence (AI). By giving real-time data on vital elements like soil moisture, temperature, humidity, and plant health, smart sensors are transforming precision agriculture. Farmers can better control fertilizers, optimize irrigation, and monitor crop conditions by integrating these sensors with IoT and AI technologies. This contributes to resource conservation, increased crop yields, and addressing environmental issues (Soussi et al., 2024). In general, smart sensors assist in addressing issues related to global agriculture, including depletion of resources, climate change, and rising food production demands.

In general, smart sensors help address problems associated with global agriculture, such as resource depletion, climate change, and increased need for food production. Furthermore, these sensors have started to become extremely important in cattle farming. For example, smart sensors assist farmers in ensuring the comfort and welfare of their livestock by keeping an eye on environmental factors like temperature and air quality in animal housing. Thus, healthier animals and lower veterinary expenses can be achieved by preventing heat stress and disease outbreaks(Terence et al., 2024).

The physical characteristics of cattle, such as weight and body dimensions, can be monitored non-invasively using Computer Vision (CV)-Based Sensors, which are frequently combined with AI algorithms. Since no direct contact is required, methods like RGB picture analysis and 3D point cloud offer great accuracy and can lessen animal suffering (Ma et al., 2024). These technologies have the potential to greatly increase the accuracy of data gathered for monitoring, enabling better cattle care and management. However, small-scale farms face difficulties due to the complexity of establishing computer vision systems, which sometimes require pricey hardware and intricate data processing (Terence et al., 2024). High initial investments are needed for computer vision systems, especially those that use 3D cameras and intricate algorithms. Particularly for smaller farms, the expense of high-quality technology (such as RGB cameras or 3D scanners) and the required computer infrastructure can be prohibitive.

CV-based systems not only provide budgetary difficulties but also demand specialized staff to properly run and maintain the technology. Farmers may find it difficult to handle system calibrations and solve problems if they lack technical skills. This could lead to erroneous data collecting and less-than-ideal herd management results. Furthermore, the accuracy of the system may be reduced in real-world situations due to environmental conditions like dust, lighting, or even the movement of the animals that impair sensor performance (Ma et al., 2024). Research is being done to make these technologies more resilient and affordable as they develop, so smaller operations can use them. Nonetheless, these technologies have a great deal of promise to improve livestock monitoring by lowering stress and increasing management effectiveness, even in the face of obstacles.

2.3 Image Processing and Machine Learning for Weight Estimation

2.3.1 Historical Development

In traditional livestock management, weight estimation was primarily performed manually using techniques such as Body Condition Scoring (BCS). This method evaluates the fatness or thinness of animals through visual inspection and tactile assessment (Bercovich et al., 2013). While straightforward and cost-effective, BCS relies heavily on the evaluator's expertise, introducing variability and potential bias in results. Additionally, this method does not provide precise numerical weight values, making it less reliable for data-driven decision-making in modern farming practices.

Before the introduction of digital technologies, farmers used scales or manual measurements to estimate livestock weight. With scales, animals were weighed directly, but this required significant infrastructure, such as livestock-specific weighing platforms. These setups were costly, labor-intensive, and often stressful for the animals, impacting their health and productivity.

For situations where scales were unavailable, farmers traditionally estimated pig weight using a tape measure and mathematical formulas. This approach involved measuring specific dimensions of the pig, such as its girth and length, and applying an empirical formula to estimate its weight. For example, pig weight can be approximated using the formula:

$$Weight(kg) = \frac{Girth(cm)^2 * Length(cm)}{400} \tag{1}$$

Where *Girth* is the circumference of the pig's chest behind the front legs, and *Length* is the distance from the base of the tail to the middle of the ears.

This method, though simpler than using scales, is prone to human error and variability in measurements. Despite its limitations, it remains popular, especially in rural farming contexts in the Philippines, where such techniques are both accessible and practical

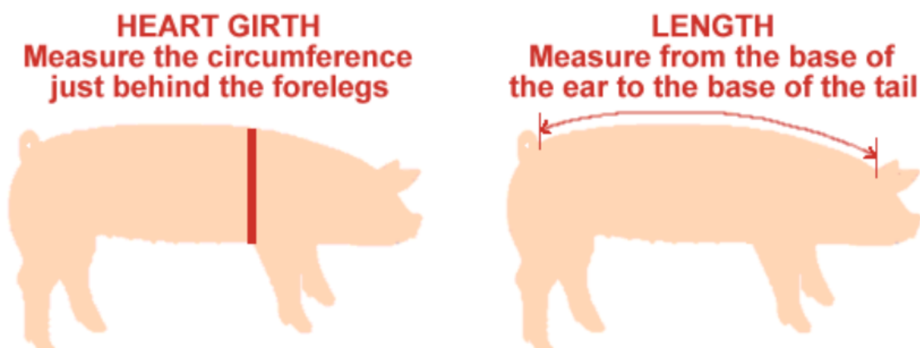

Figure 1: Illustration of weight estimation using a tape measure

2.3.2 Modern Techniques

Body weight (BW) prediction in livestock can be modeled using four main approaches of increasing complexity: Traditional Approach, Computer Vision Approach, Computer Vision with Machine Learning, and Computer Vision with Deep Learning. The Traditional Approach relies on manually collected morphometric measurements such as heart girth, wither height, and body length, which are then applied in traditional regression models. This method has been widely used for species such as cattle, pigs, sheep, goats, camels, and yaks (Franco et al., 2017); (Fadlelmoula et al., 2020); (Yan et al., 2019). While effective, it is labor-intensive and causes stress to the animals. To mitigate these issues, the Computer Vision (CV) Approach uses 2D and 3D electro-optical sensors, such as RGB or Kinect cameras, to capture images for morphometric measurements (Ozkaya, 2013). Although 3D cameras improve precision, they are expensive and require complex data processing. The CV with Machine Learning (CV+ML) Approach enhances the CV method by automating feature selection with machine learning techniques, although some manual processes, such as image segmentation and morphometric extraction, remain necessary (Tasdemir and Ozkan, 2019). Finally, the CV with Deep Learning (CV+DL) Approach uses deep learning models, including convolutional neural networks (CNNs) and recurrent convolutional networks (RCNNs), to fully automate the BW prediction process (Gjergji et al., 2020). While this approach has shown significant improvements, challenges still exist in precisely segmenting animals from complex backgrounds (Shukla and Anand, 2016). These approaches highlight the evolution of BW prediction models, transitioning from manual methods to fully automated systems, with deep learning offering promising advancements.

2.3.3 Applications of Kinect in Agriculture

In livestock farming, Kinect sensors are used to monitor animal behavior, health, and growth through 3D imaging. This technology allows for early detection of health issues by analyzing subtle changes in posture, gait, and movement patterns. It can identify lameness in cattle early on, allowing for prompt intervention (Singh et al., 2022). Moreover, Kinect's non-invasive methods provide automated weight estimation by capturing 3D images, reducing the need for stressful manual weighing processes. Continuous monitoring helps track growth and optimize feeding schedules, contributing to the overall welfare of livestock. In addition to health monitoring, Kinect sensors contribute to environmental control within livestock facilities, tracking variables like temperature and humidity to ensure optimal conditions. In poultry farming, Kinect can monitor flock movement patterns, alerting farmers to potential issues like overcrowding, which could lead to health or productivity problems.

The integration of Kinect into Precision Livestock Farming (PLF) systems further enhances its value, as it collects real-time data alongside other technologies like RFID and GPS. This combination allows for more efficient resource management, improved reproductive tracking, and more precise feeding practices (Monteiro et al., 2021). Kinect technology is also being used in crop management. Its 3D imaging capabilities are beneficial in monitoring plant growth, detecting diseases early, and optimizing resource use like water and fertilizers. In automated harvesting, Kinect sensors guide robots through fields, identifying ripe crops based on their size and shape. This reduces the need for manual labor and ensures timely harvesting to maximize yield and quality (Singh et al., 2022).

2.4 Microsoft Kinect V1

The Kinect V1 sensor employs an infrared (IR) structured light system to capture depth information. It consists of three main components: an RGB camera, an IR projector, and an IR sensor. The RGB camera captures standard color images, while the IR projector emits a structured pattern of infrared light onto the environment. The IR sensor detects distortions in the projected pattern caused by objects in the scene, enabling the device to compute depth information based on the time and spatial displacement of the reflected IR light (Zhang, 2012). This technique provides a depth resolution of 640x480 pixels, with a frame rate of up to 30 frames per second, making it suitable for capturing detailed spatial data.

2.4.1 Depth Data Acquisition and Processing

The Kinect V1 produces a 3D point cloud by combining depth and RGB data, representing the spatial coordinates (X, Y, Z) of each pixel in the captured scene. This depth information is particularly useful for applications requiring precise measurements of object size, shape, and volume. The sensor's effective depth range is between 0.8 and 4.0 meters, allowing it to capture accurate data within typical livestock pen dimensions (Smisek et al., 2013). By leveraging its depth-sensing capability, researchers can measure the dimensions of objects without physical contact, making it ideal for non-invasive weight estimation in pigs.

2.4.2 Kinect V1 Applications in Agriculture

The Kinect V1 has been successfully utilized in agricultural studies for tasks such as plant phenotyping, fruit grading, and livestock monitoring. For instance, (Andújar et al., 2016) used the Kinect V1 to evaluate crop height and canopy structure, demonstrating its utility in capturing detailed morphological data. Similarly, (Pezzuolo et al., 2018) employed the Kinect V1 to estimate cattle body volume and weight, achieving high accuracy compared to traditional methods. These applications highlight the potential of the Kinect V1 as a versatile tool for precision agriculture.

2.4.3 Kinect V1 Potential for Pig Weight Estimation

In pig farming, accurate weight estimation is crucial for optimizing feeding strategies and monitoring growth. Traditional weighing methods, such as scales or manual measurements, can be labor-intensive, stressful for animals, and prone to errors (Faucitano and Goumon, 2018). The Kinect V1 offers a non-invasive alternative by capturing detailed depth images that enable the calculation of pig body volume. By processing these depth images using machine learning algorithms, it is possible to develop a system that estimates pig weight based on 3D body volume, eliminating the need for physical contact.

The Kinect V1's structured light technology ensures that depth measurements are unaffected by variations in visible light conditions, making it suitable for use in indoor pig pens where lighting may vary. Additionally, its ability to provide real-time depth data opens the possibility for developing dynamic weight monitoring systems that can track pig growth continuously.

2.5 Synthesis Matrix

The synthesis matrix provides valuable insights into pig weight estimation methods using various imaging and analysis techniques. Together, these studies provide a cohesive foundation for applying Kinect technology, advanced imaging, and regression methods in the current study, demonstrating approaches for accurate, adaptable, and practical pig weight estimation.

Table 1: Synthesis Matrix

Title	**Author(s), Year**	**Methodology**	**Findings**	**Relevance**
On-barn pig weight estimation based on body measurements by a Kinect v1 depth camera	Pezzuolo, A., Guarino, M., Sartori, L., González, L. A., and Marinello, F. (2018)	- Kinect v1 Depth Camera - Estimated pig weight from body measurements - Captured 3D images in a barn environment - Extracted length, width, and volume from depth data - Developed a regression model for weight estimation	Both linear and second-degree regression models showed strong correlations with reference weights, with coefficients of determination above 0.95. The non-linear model reduced the standard error by half, and the second-degree regression model had an absolute error of less than 0.5 kg.	The current study is closely correlated with this study, especially in terms of the usage of the Kinect v1 camera. This study, however, uses 3D images for the calculation of estimated weights.

Pig Weight Estimation According to RGB Image Analysis	Andras Kárpinszky, Gergely Dobsinszki(2023)	- RGB Cameras (Dahua Models) - RGB image captured above pig pens - Mask R-CNN for segmentation - Kalman filters for tracking - Pretty Contour Picker (PCP) for filtering - Weight estimation using Multi-Layer Perceptron (MLP)	The system achieved more than 97 percent accuracy in predicting pig weights compared to manually recorded weights. Among the models tested, Model V2 was the most consistent, providing high accuracy across varying weight ranges. The RGB image-based method allows faster and stress-free weight measurement, which is valuable for decision-making in pig farming	Although a Kinect camera wasn't used in the study, the setup for data acquisition and processing is similar. Top-view photos of pigs were also used in this study, closely relating to how the current study takes them.

Estimating Pig Weights from Images without Constraint on Posture and Illumination	Kyungkoo Jun, Si Jung Kim, Hyun Wook Ji (2018)	- 2D Image Processing - No relaxed posture and illumination constraints - Image processing: binarization, morphological ops, contour analysis - Features: area size, curvature, deviation - Neural network model trained and tested for weight prediction	The study achieved an average estimation error of 3.15 kg and a coefficient of determination (R^2) of 0.792. Despite this being lower than previous works, the method was able to estimate pig weights without controlling the environment, posture, or lighting, making it applicable in less constrained settings. The model showed that posture-related features contributed significantly to weight prediction accuracy.	The study utilized a 2D camera, meanwhile the current study will utilize a Kinect v1 camera. Despite the difference, both studies have similar top-down view camera setups. The idea of estimating pig weights without constraints on posture and illumination can also be an inspiration for future similar undertakings with the Kinect v1 camera.

Carcass Quality Traits of Fattening Pigs Estimated Using 3D Image Technology	A. Peña Fernández, T. Norton, E. Vranken, D. Berckmans (2019)	- Kinect 3D Cameras - Capture 3D top-view images pre-slaughter. - Extract image features: lengths, areas, and volumes. - MATLAB for stepwise linear regression analysis	The regression models achieved an adjusted R^2 ranging from 70-85 percent during training, but performance decreased to 50-60 percent during validation. The best correlations with slaughter traits, such as final weight and yield, were found using the median values of image features from the last week of the fattening period.	Considering only the sections relevant to pig weight estimation, the study can be used as a reference for the current study given that it also uses Kinect cameras for image capture. The methods for feature extraction and pig weight estimation and analysis can be used as one of the bases for the methods that will be used in the current study.

The synthesis matrix provides valuable insights into pig weight estimation methods using various imaging and analysis techniques. The first study by (Pezzuolo et al., 2018) effectively demonstrates using a Kinect v1 depth camera to capture 3D body measurements, achieving high prediction accuracy with regression models, particularly a second-degree regression model that reduced error to under 0.5 kg. This finding supports the current study's use of Kinect v1 for accurate weight estimation via 3D imaging.

In another study, (Kárpinszky and Dobsinszki, 2023) employed RGB cameras combined with segmentation (Mask R-CNN) and MLP models, achieving over 97 percent accuracy in weight prediction. Although RGB cameras differ from Kinect, the segmentation and tracking methods align well with the current study's top-view imaging approach and offer potential techniques for data processing in the project.

The work of (Jun et al., 2018) further broadens applicability by achieving weight estimation without controlling for pig posture or lighting, using a neural network model on 2D images with a 3.15 kg error margin. This flexibility offers useful insights into handling environmental variability, which could enhance the robustness of your Kinect-based approach.

Lastly, (Peña Fernández et al., 2019) applied Kinect-based 3D imaging for carcass trait prediction, with results showing time-evolving feature accuracy between 50-85 percent. Their regression techniques could be useful for refining the project's model to predict weight accurately. Together, these studies provide a cohesive foundation for applying Kinect technology, advanced imaging, and regression methods in the current study, demonstrating approaches for accurate, adaptable, and practical pig weight estimation.

CHAPTER 3

METHODOLOGY

This chapter presents the research methodology used in the study, it covers the in-depth details of the procedures and steps taken in the research design, design procedure, system development, and deployment process of this study.

3.1 System Architecture

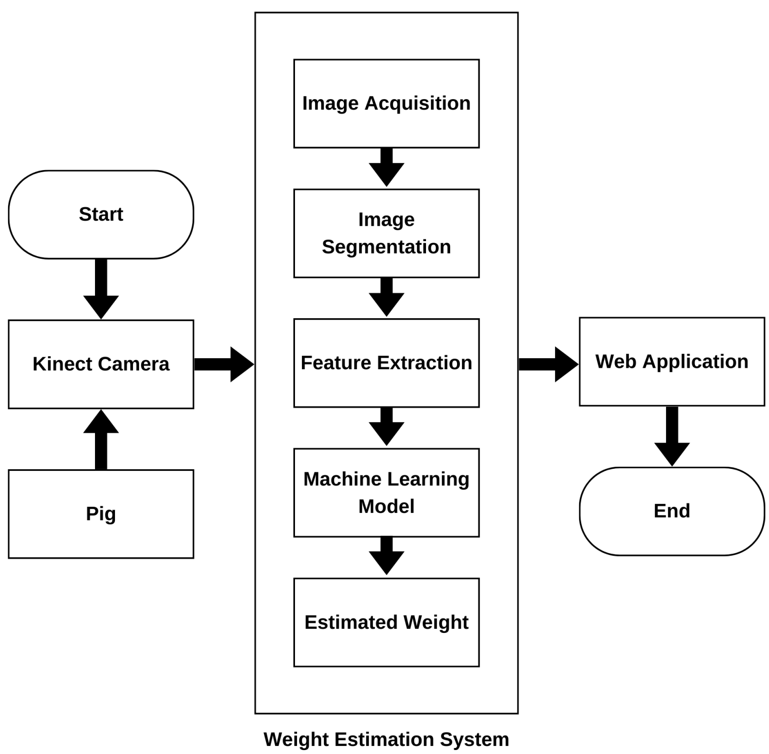

Figure 2: System Architecture

Figure 2 shows the system architecture of the pig weight estimation system. It consists of the pig to be captured, the Kinect camera that will be used for taking depth images, and the system for the processing of all the data. A laptop will be used for the processing of data, which will include the processing of images, extraction of pig's features, and calculation of estimated weight with a machine learning model. The result can then be accessed in a web application, where actual and estimated weights can be validated.

3.1.1 Waterfall Model

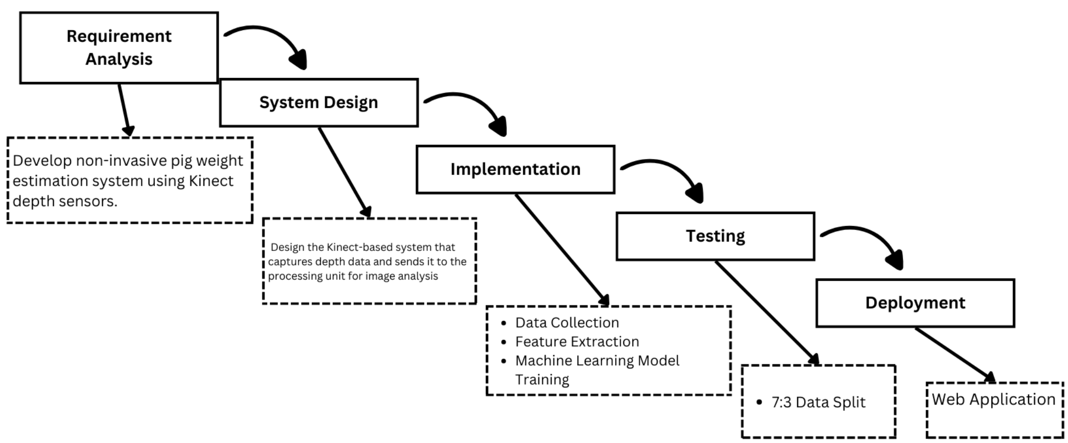

Figure 3: Waterfall Model

Figure 3 shows the Waterfall Model of the Weight Estimation System. Requirement Analysis, defines the goal for creating a non-invasive pig weight estimation system using a Kinect depth sensor. The system captures depth images, extracts features like height and volume, and predicts weight through machine learning models, with results available via a web app. System Design plans the architecture, including hardware and software components. For the hardware components, a Kinect sensor, a computer system, and a pig pen setup are required. While a Machine learning model and a web application is required for the software components. Implementation involves collecting images, extracting features, and training machine learning models. The Kinect sensor gathers the images to be processed. An algorithm extracts the features such as the height, area and volume from the depth images. The image processing involves grayscale conversion of the gathered images, contour detection and feature segmentation to isolate pig features. The training of the machine learning model follows a ratio of 7:3 for the training data and the testing data respectively. The testing phase assesses the system's accuracy using performance metrics such as MAE and RMSE. Following the 7:3 ratio, 30 percent of the gathered data set is used in the testing of the machine learning models in which the most accurate model is selected. The system is deployed using a web application that displays the weight estimates based on input depths.

3.1.2 Flowchart

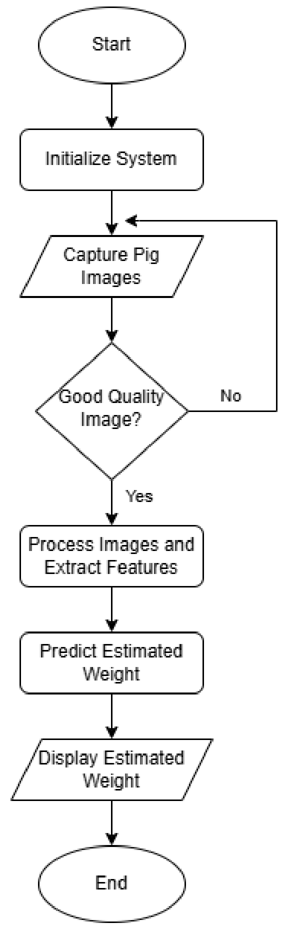

Figure 4: Flowchart

Figure 4 outlines the flowchart of the weight estimation system. The process begins with system initialization, where the Kinect camera and other equipment are powered on, and the pig is prepared for imaging. Images are captured using the Kinect camera, and a good quality image is defined as clear, well-lit, free of motion blur, and accurately representing the pig's dimensions.

To select the highest quality image, a max voting ensemble algorithm evaluates multiple captured images based on metrics like sharpness, contrast, and brightness (Gonzalez and Woods, 2018). If no satisfactory image is found, additional captures are made until a quality image is obtained. Once a high-quality image is secured, the system moves on to image preprocessing and feature extraction, leading to the prediction of the estimated weight. The final result is then displayed in a web application for user access.

3.1.3 Pigpen Diagram

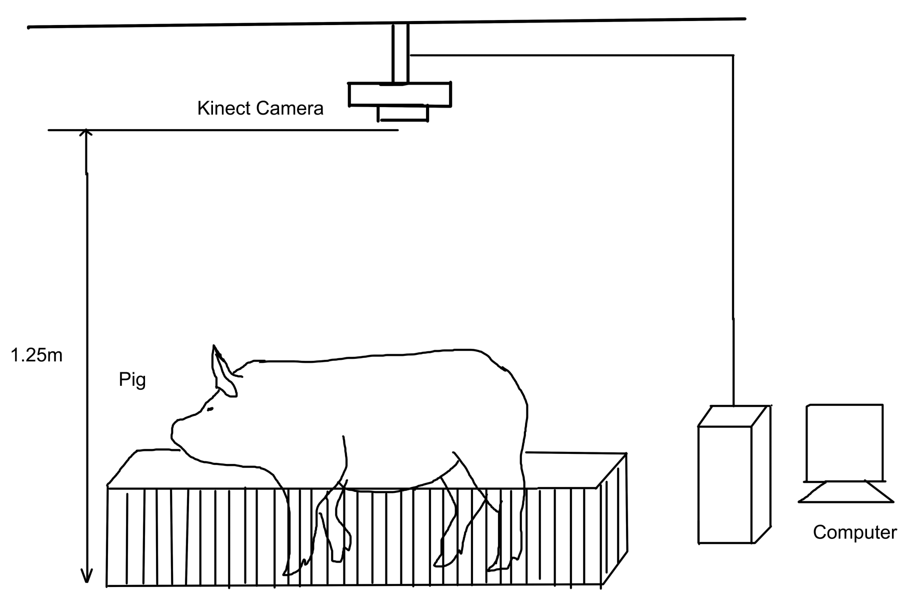

Figure 5: Pigpen Diagram

Figure 5 presents a diagram of the pigpen, illustrating the positioning of the Kinect camera. The camera is strategically suspended 1.25 meters above the ground. This height ensures a clear capture of the pig within the pen, while remaining low enough to minimize the likelihood of capturing workers as they move around the area. Additionally, this positioning keeps the camera within its optimal range of 2 meters, maximizing its effectiveness for monitoring purposes. This setup is designed to predict the weight of one pig at a time

3.2 Study Design and Data Collection

The study will be conducted in commercial pig weaning farms located in Northern Mindanao, Philippines, focusing on pigs of the Landrace breed. These pigs, with an average live weight ranging from 40 to 100 kilograms, are fed using commercial dry pellet feed and have access to water through standard feeders in the weaning pens. Data collection will take place within these farms, where depth images of the pigs will be captured using the Kinect V1 camera. The camera will record depth data, essential for calculating the distance between the sensor and the top of the pig, and between the sensor and the ground. This is needed for the calculation of the height of the pig, which will be used to estimate the pig's weight. Several environmental factors will also be monitored during data collection, such as lighting conditions and temperature. The size of the pen in the weaning barn will be recorded to ensure consistent environmental conditions for all pigs observed. Additionally, the temperature of the area during observation will be measured, as fluctuations in temperature can influence the pigs' behavior and posture. The lighting conditions within the observation area will also be documented, given that lighting can impact the quality of the depth images captured by the Kinect sensor. By controlling and documenting these variables, the study aims to minimize external factors that could affect the accuracy of the weight estimation model.

3.3 Object Detection

Object detection in this study isolates the pig within each frame using depth images from Kinect sensors to identify the region of interest (ROI). We employ YOLOv11 (You Only Look Once, version 11), a state-of-the-art single-shot object detection model that delivers superior efficiency and accuracy in real-time applications.

YOLOv11 incorporates several advanced features that make it ideal for agricultural applications, including pig detection. It utilizes an improved backbone and neck architecture, significantly enhancing its feature extraction capabilities. This enhancement allows the model to handle complex object detection tasks, such as identifying pigs with varying poses and sizes, with higher precision. Additionally, YOLOv11 introduces refined architectural de-signs and optimized training pipelines, achieving faster processing speeds without compromising accuracy, making it highly suitable for real-time detection in a dynamic farm environment.

The model achieves a higher mean Average Precision (mAP) on benchmark datasets, such as COCO, while using 22 percent fewer parameters compared to earlier versions like YOLOv8. This computational efficiency reduces hardware requirements, enabling deployment on edge devices without sacrificing performance. Its flexibility allows seamless integration across various platforms, including edge devices, cloud systems, and NVIDIA GPU-supported hardware, ensuring adaptability to different farm setups and computational infrastructures.

Furthermore, YOLOv11 supports a broad range of computer vision tasks, including instance segmentation, image classification, pose estimation, and oriented object detection. While this study focuses on object detection, YOLOv11's versatility ensures scalability for future enhancements, making it a robust choice for agricultural applications.

A pre-trained YOLOv11 model, fine-tuned with depth image data specific to our study, was selected to leverage transfer learning. This approach minimizes training overhead and maximizes detection reliability. YOLOv11's ability to process entire images in a single pass ensures optimized speed and accuracy—key factors for real-time agricultural applications. Its enhanced feature extraction and superior accuracy make it particularly well-suited for detecting complex and variable shapes, such as pigs, in the farm environment.

3.4 Segmentation Model

This study employs the Segmentation Anything Model (SAM) to achieve precise segmentation of the pig within the detected ROI. SAM is uniquely suited for this task due to its prompt-based, generalizable approach, which allows for accurate segmentation with minimal retraining (Kirillov et al., 2023). SAM's adaptability is essential in agricultural settings, where it reliably captures complex shapes and contours, ensuring high-quality feature extraction of key metrics like height and area. By using SAM, we enhance the segmentation accuracy and efficiency, enabling more consistent and precise data for weight estimation.

3.4.1 Image Preprocessing

During the preprocessing stage, the image is converted to grayscale and resized. If its dimensions are smaller than the target size, symmetric padding is applied to ensure the entire pig is visible within the frame. Next, a Gaussian blur with a kernel size of (13,13) is applied; this kernel size is chosen arbitrarily to balance blurring and detail preservation. The blurred image is then subtracted from the original to enhance edges, expressed as follows:

$$I_{\text{sharp}}(x, y) = I(x, y) + \alpha(I(x, y) - I_{\text{blur}}(x, y)) \tag{2}$$

where I(x,y) is the original intensity and Iblur(x,y) is the blurred intensity. A threshold value of T=5 is chosen for binarization to effectively distinguish the pig's silhouette from the background; this value is determined based on preliminary testing to optimize contrast without losing important details. This preprocessing workflow ensures a standardized input for subsequent models, facilitating accurate feature extraction.

3.4.2 Slicing the Image

The image is split into upper and lower halves based on the principal direction of the pig's body. This is achieved using the eigenvalue decomposition of the covariance matrix derived from the contour points of the pig. First, the centroid of the contour is calculated using the image moments:

$$cX = \frac{M_{10}}{M_{00}}, \quad cY = \frac{M_{01}}{M_{00}} \tag{3}$$

Where $M_0 0$ is the area of the contour, and$M_1 0$, $M_0 1$ are the first-order moments along with the x and y axes, respectively. The covariance matrix σ of the contour points is then computed as:

$$\Sigma = \frac{1}{N}\sum_{i=1}^{N}(p_i - \mu)(p_i - \mu)^T \tag{4}$$

Where p_1 represents a contour point, μ is the mean of the contour points, and N is the total number of points. The eigenvector corresponding to the largest eigenvalue defines the primary direction along which the image is sliced. The eigenvector, $v = [v_x, v_y]^T$, is used to define the slope of the line that divides the pig into upper and lower halves:

$$y_line(x) = \frac{v_y}{v_x}(x - cX) + cY \tag{5}$$

After slicing, gaps in the binary mask are filled using a morphological closing operation. This ensures that the segmentation is continuous, filling any small holes that might have been created during slicing.

$$I_{\text{filled}} = I_{\text{mask}} \oplus K \tag{6}$$

where K is a kernel of size (5,5) used for morphological closing.

3.4.3 Valley Detection

To segment the pig into distinct anatomical regions (head, body, legs), we detect valleys along the contour. Valleys correspond to local minima in the pig's contour, typically where the legs meet the body or the neck separates the head from the shoulders. First, we extract the outline of the pig and smooth the contour using linear interpolation. The interpolated contour points are then analyzed using peak detection on the inverted y-coordinates to find the valleys, representing the points of maximum curvature. let $(x_i, y_i)_i^N = 1$ represent the sorted interpolated contour points. The valleys are found by identifying the local maxima in the inverted contour:

$$v_i = argmax(-y(x)) \tag{7}$$

The detected valleys are sorted based on their xxx-coordinates to establish the segmentation boundaries.

3.4.4 Segmentation into Sections

Using the detected valleys, we define four primary sections: legs, body, shoulders, head. Each section is extracted by crearing binary masks between consecutive valleys:

$$S_region(x, y) = I_sharp(x, y)(1_[x_start, x_end]) \tag{8}$$

where S_region is the segmented region of interest.

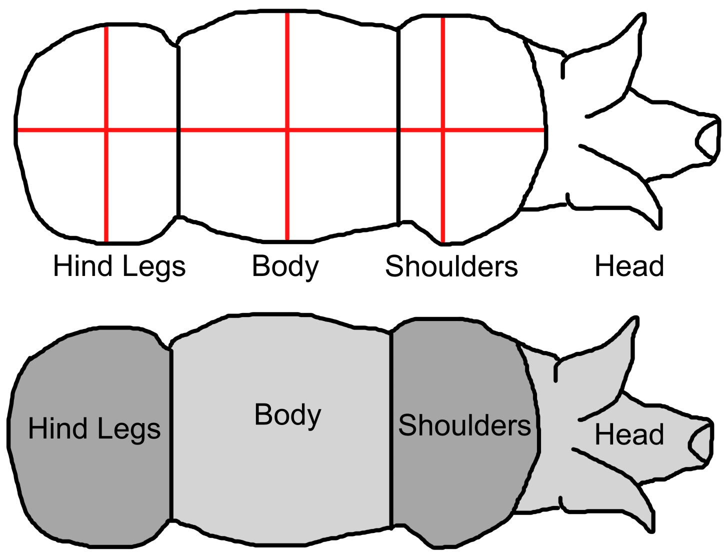

Figure 6: Schematic representation of segmentation

Figure 5 shows a schematic representation of the segmentation of the pig. Following the segmentation process found in the study conducted by, the pig is segmented into four distinct parts: the hind legs, body, shoulder, and head. Using this segmentation framework, an algorithm will be developed to accurately divide the pig into these four areas. This is due to the difference in the pigs overall shape, allowing for more detailed data analysis and improved precision in data collection.

3.5 Feature Extraction

After segmentation, depth information is used to extract key features from the pig's body. The Kinect sensor provides depth data $D(x, y)$, where the $x - axis$ and $y - axis$ represent the horizontal and vertical pixel coordinates of each point on the pig's body, respectively. This data indicates the distance between the sensor and a specific point on the pig at a given pixel location (x, y). Important features derived from this data include height, age, area, and gender.

3.5.1 Height Extraction

The height of the pig is determined by finding the maximum and minimum depth values within the segmented region. Let S(x,y) be the segmented mask of the pig. The height is calculated as:

$$x_{\text{highest}} = \max\{D(x, y) \mid (x, y) \in S(x, y)\} \tag{9}$$

$$x_{\text{lowest}} = \min\{D(x, y) \mid (x, y) \in S(x, y)\} \tag{10}$$

$$y_{\text{height}} = x_{\text{highest}} - x_{\text{lowest}} \tag{11}$$

where $x_highest$ denotes the highest intensity and x_lowest denotes the lowest intensity $S(x, y)$.

3.5.2 Area Extraction

The area occupied by the pig in the image is calculated by counting the number of pixels in the segmented region:

$$Area = \sum_{(x,y) \in S(x,y)} 1 \tag{12}$$

The area corresponds to the total number of pixels within the segmented pig's contour, representing the surface area in the depth image.

3.5.3 Gradient Information from Depth Data

The depth gradient across the pig's body provides additional insight into the pig's shape. The gradient of the depth image D(x,y) can be computed using the finite difference approximation:

$$\delta(x,y) = (\frac{\partial}{\partial x}, \frac{\partial}{\partial y}) \tag{13}$$

This gradient gives us information about the slope of the pig's body, which can be used to under more detailed features such as the body curvature and the slope of different anatomical regions. The gradient magnitude can be used to detect regions of rapid change in depth, such as the transition from the pig's back to its sides:

$$|\delta(x,y)| = \sqrt{\left(\frac{\partial}{\partial x}\right)^2 + \left(\frac{\partial}{\partial y}\right)^2} \tag{14}$$

3.6 Model Training

In the model training phase, the extracted features will serve as inputs to various regression models aimed at estimating pig weight. We will explore several algorithms to identify the most accurate model for weight estimation: Linear Regression, Ridge Regression, Decision Trees, LightGBM, and XGBoost.

The analysis begins with linear regression, which models the linear relationship between features and weight, providing a straightforward baseline for comparison with more complex models (Mullainathan and Spiess, 2017). Ridge regression will be employed as an extension of linear regression, incorporating L2 regularization to mitigate overfitting, especially in cases of multicollinearity among input features. This approach enhances robustness against noisy data (Tikhonov, 1963).

Decision trees will also be utilized for their interpretability and ability to capture complex relationships within the data, though they require careful tuning to avoid overfitting (Breiman et al., 1986). LightGBM (Light Gradient Boosting Machine) is included for its efficiency and scalability with large datasets, utilizing a histogram-based learning approach to achieve faster training and improved accuracy (Ke et al., 2017). Additionally, XGBoost (Extreme Gradient Boosting) will be assessed for its high performance and optimizations for handling missing values and regularization, making it a leading choice in competitive machine-learning environments (Chen and Guestrin, 2016). Model performance will be evaluated using metrics such as Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). MAE provides a clear measure of average error, while RMSE emphasizes larger errors, facilitating a comprehensive assessment of the model's accuracy (Willmott and Matsuura, 2005).

3.7 Evaluation

The trained models will undergo rigorous evaluation using a dedicated test dataset, comprising previously unseen data sampled randomly, which constitutes 30 percent of the overall dataset. This approach ensures that the evaluation accurately reflects the model's ability to generalize to new instances rather than merely memorizing the training data.

3.7.1 Test Dataset

By reserving 30 percent of the total dataset as the test dataset, we establish a method for assessing model performance. This test dataset will not have been exposed to the models during training, which is crucial for evaluating how well the models can predict weights on new data. The random sampling method ensures a representative distribution of weights and features, allowing for a fair assessment of the model's predictive capabilities.

3.7.2 Performance Metrics

To quantitatively evaluate the models, we will utilize the following performance metrics: Mean Absolute Error (MAE). MAE calculates the average absolute difference between the actual values and the predicted values. It is a robust metric that does not penalize larger errors as heavily as MSE, making it more appropriate for interpreting the accuracy of regression models. The formula for MAE is:

$$MAE = \frac{1}{N} \sum_{t=1}^{N} |\hat{y}_t - y_t| \tag{15}$$

The MAE metric gives a straightforward interpretation of error, as it expresses the average error directly in terms of the target variable (i.e., weight). It also equally weights all errors, making it a preferred choice for evaluating models that must perform reliably across a range of errors.

3.7.3 Root Mean Squared Error (RMSE)

RMSE provides a measure of how well the model's predictions match the actual data, expressed in the same units as the target variable. It is particularly useful as it penalizes larger errors more heavily, making it sensitive to outliers. The equation for RMSE is given by:

$$RMSE = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (y_t - \hat{y}_t)^2} \tag{16}$$

Where n is the number of observations in the test dataset, yi is the actual weight of the pig for the t-th observation, and yi is the predicted weight of the pig for the t-th observation.

3.8 Testing Method

The trained model will undergo rigorous evaluation to validate its accuracy. This evaluation will involve a cross-validation process utilizing a new set of pigs in a real-world experimental setup. The experimental process includes testing the system by comparing the predicted weights to the actual weights obtained using a traditional weighing scale. This approach ensures that the model is tested under practical farming conditions and its results are benchmarked against ground truth values.

3.9 Location

The experimental testing will take place at a backyard pig-weaning farm in El Salvador City, Misamis Oriental, Philippines. This location was selected due to its accessibility and suitability for the study. The study will focus on Landrace pigs, a breed well-suited for controlled weight estimation studies, with an average weight range of 40–100 kg. Environmental variables such as lighting, temperature, and pen dimensions will be monitored to ensure consistent conditions throughout the testing period.

3.10 Data Collection

The Kinect sensor will be mounted in a fixed position above the pigpen to capture real-time depth images of the pigs. The system will continuously monitor the pigs and process images in real time to estimate their weight. Each depth image captured by the Kinect sensor will undergo preprocessing to ensure it meets the quality standards required for accurate feature extraction. Low-quality images, such as those affected by motion blur or poor lighting, will be automatically filtered out by an image quality check embedded in the system.

Once an acceptable image is identified, the system will extract features such as body height, surface area, and volume directly from the depth data. These features will then be inputted into a pre-trained machine-learning model to predict the pig's weight instantly. The estimated weight will be displayed in real time on a connected interface, such as a web application, for immediate validation and monitoring.

The Kinect sensor will be calibrated at the start of the observation period. This calibration will account for environmental factors such as lighting conditions and the sensor's positioning relative to the ground. For validation purposes, the predicted weight from the system will be periodically compared to the reference weight measured using a traditional weighing scale. These comparisons will be conducted during specific intervals to ensure the accuracy and consistency of real-time predictions.

3.11 Experimental Setup

The experiment aims to evaluate the system's accuracy in real-time pig weight prediction under controlled conditions. The setup includes a Kinect sensor, a computing unit, and a software pipeline for processing depth data and predicting pig weights. The details of the experimental setup are as follows:

3.11.1 Environment Preparation

Pigpen Setup. The experiment will take place in a typical pigpen environment to simulate real-world conditions. The area will be cleared of obstructions to ensure the Kinect sensor has an unobstructed view of the pigs.

Lighting Conditions. Ambient lighting will be adjusted to minimize shadows and reflections. While the Kinect sensor primarily uses depth imaging, consistent lighting supports system calibration and overall reliability.

Sensor Placement. The Kinect sensor will be mounted overhead, approximately 1.25 meters above the ground, ensuring a clear top-down view of the pigs. The mounting structure will be stable to prevent movement during the experiment.

3.11.2 Kinect Sensor Calibration

Height and Angle. The sensor will be carefully positioned, 1.25 meters from the ground, to ensure its depth camera captures accurate data, with the angle adjusted to be perpendicular to the ground.

Validation with Calibration Objects. Objects of known dimensions will be placed within the pigpen to verify the sensor's accuracy in capturing depth and spatial measurements.

3.11.3 Data Collection and Processing

Image Capture. The Kinect sensor will continuously capture depth images of pigs moving naturally within the pen. These images will be processed in real time to extract relevant features.

Feature Extraction. Using depth images, the system will extract features critical to weight prediction, including:

Body Height: The vertical measurement of the pig from the ground.

Surface Area: The top-down projected area of the pig.

Volume: Estimated using depth data to represent the pig's three-dimensional structure.

Weight Prediction. Extracted features will be fed into a pre-trained machine learning model that predicts the pig's weight. The model is based on historical data correlating these features with known weights.

3.11.4 Accuracy Evaluation

Reference Weights. A subset of pigs will be manually weighed using a calibrated digital scale to provide ground truth measurements. These reference weights will be used to assess the accuracy of the system's predictions.

Performance Metrics. The predicted weights will be compared against the reference weights using the following statistical measures:

Mean Absolute Error (MAE): Indicates the average absolute deviation of predictions from the true values.

Root Mean Square Error (RMSE): Highlights the magnitude of prediction errors, emphasizing larger discrepancies.

Correlation Coefficient (R^2): Evaluates the strength and reliability of the relationship between predicted and actual weights.

Repeated Measurements. To ensure consistency, weight predictions will be recorded multiple times for each pig under varying activity levels (e.g., standing, lying down) and averaged to minimize variability.

3.11.5 Validation Process

The experiment will be conducted in several sessions, with data collected from different pigs of varying sizes to evaluate the system's ability to generalize. Results will be analyzed to identify any systematic errors, such as over- or under-prediction for specific weight ranges, and adjustments will be made to the machine learning model if necessary.

References

Andújar, D., Escolà, A., and Rosell-Polo, J. R. (2016). A review of optical sensing systems for plant phenotyping. *Precision Agriculture*, 17(1):1–18.

Bercovich, A., Edan, Y., Alchanatis, V., Moallem, U., Parmet, Y., Honig, H., Maltz, E., Antler, A., and Halachmi, I. (2013). Development of an automatic cow body condition scoring using body shape signature and fourier descriptors. *Journal of dairy science*, 96(12):8047–8059.

Dickinson, R., Morton, J., Beggs, D., Anderson, G., Pyman, M., Mansell, P., and Blackwood, C. (2013). An automated walk-over weighing system as a tool for measuring liveweight change in lactating dairy cows. *Journal of dairy science*, 96(7):4477–4486.

Dikmen, S., Ustuner, H., and Orman, A. (2012). The effect of body weight on some welfare indicators in feedlot cattle in a hot environment. *International journal of biometeorology*, 56:297–303.

Dohmen, R., Catal, C., and Liu, Q. (2022). Computer vision-based weight estimation of livestock: a systematic literature review. *New Zealand journal of agricultural research*, 65(2-3):227–247.

Fadlelmoula, A. A., Mudarris, M. S., and Hariri, M. S. (2020). Prediction of live body weights in dromedary camels (camelus dromedarius) from morphometric body measurements. *World journal of biology and biotechnology*, 5(1):25–29.

Faucitano, L. and Goumon, S. (2018). Transport of pigs to slaughter and associated handling. In *Advances in pig welfare*, pages 261–293. Elsevier.

Food and Agriculture Organization (FAO) (2022). Global meat consumption statistics. `http://www.fao.org`. Accessed: 2024-12-06.

Franco, M. d. O., Marcondes, M. I., Campos, J. M. d. S., Freitas, D. R. d., Detmann, E., and Valadares Filho, S. d. C. (2017). Evaluation of body weight prediction equations in growing heifers. *Acta Scientiarum. Animal Sciences*, 39(2):201–206.

Gjergji, M., de Moraes Weber, V., Silva, L. O. C., da Costa Gomes, R., De Araújo, T. L. A. C., Pistori, H., and Alvarez, M. (2020). Deep learning techniques for beef cattle body weight prediction. In *2020 International Joint Conference on Neural Networks (IJCNN)*, pages 1–8. IEEE.

Gómez, Y., Stygar, A. H., Boumans, I. J., Bokkers, E. A., Pedersen, L. J., Niemi, J. K., Pastell, M., Manteca, X., and Llonch, P. (2021). A systematic review on validated precision livestock farming technologies for pig production and its potential to assess animal welfare. *Frontiers in veterinary science*, 8:660565.

Jun, K., Kim, S. J., and Ji, H. W. (2018). Estimating pig weights from images without constraint on posture and illumination. *Computers and Electronics in Agriculture*, 153:169–176.

Kárpinszky, A. and Dobsinszki, G. (2023). Pig weight estimation according to rgb image analysis.

Kollis, K., Phang, C. S., Banhazi, T. M., and Searle, S. J. (2007). Weight estimation using image analysis and statistical modelling: A preliminary study. *Applied engineering in agriculture*, 23(1):91–96.

Li, Z., Luo, C., Teng, G., and Liu, T. (2014). Estimation of pig weight by machine vision: A review. In *Computer and Computing Technologies in Agriculture VII: 7th IFIP WG 5.14 International Conference, CCTA 2013, Beijing, China, September 18-20, 2013, Revised Selected Papers, Part II 7*, pages 42–49. Springer.

Ma, W., Qi, X., Sun, Y., Gao, R., Ding, L., Wang, R., Peng, C., Zhang, J., Wu, J., Xu, Z., et al. (2024). Computer vision-based measurement techniques for livestock body dimension and weight: A review. *Agriculture*, 14(2):306.

Mañez, M., Ortega, J., and Aguilar, D. (2020). Performance evaluation of pig breeds in the philippines: A study on landrace pigs. *Philippine Agricultural Science*, 103(3):217–225.

Monteiro, A., Santos, S., and Gonçalves, P. (2021). Precision agriculture for crop and livestock farming—brief review. *Animals*, 11(8):2345.

Neethirajan, S. and Kemp, B. (2021). Digital livestock farming. *Sensing and Bio-Sensing Research*, 32:100408.

Ng, W. C., Soong, Y. Q., and Teh, S. Y. (2023). Machine learning in food security and sustainability. In *Handbook of Sustainability Science in the Future: Policies, Technologies and Education by 2050*, pages 1583–1599. Springer.

Ozkaya, S. (2013). The prediction of live weight from body measurements on female holstein calves by digital image analysis. *The Journal of Agricultural Science*, 151(4):570–576.

Peña Fernández, A., Norton, T., Vranken, E., and Berckmans, D. (2019). Carcass quality traits of fattening pigs estimated using 3d image technology. In *proceedings of the 9th European Conference on Precision Livestock Farming*. ECPLF.

Pezzuolo, A., Guarino, M., Sartori, L., González, L. A., and Marinello, F. (2018). On-barn pig weight estimation based on body measurements by a kinect v1 depth camera. *Computers and electronics in agriculture*, 148:29–36.

Rousing, T., Bonde, M., Badsberg, J. H., and Sørensen, J. T. (2004). Stepping and kicking behaviour during milking in relation to response in human–animal interaction test and clinical health in loose housed dairy cows. *Livestock Production Science*, 88(1-2):1–8.

Samperio, E., Lidón, I., Rebollar, R., Castejón-Limas, M., and Álvarez-Aparicio, C. (2021). Lambs' live weight estimation using 3d images. *Animal*, 15(5):100212.

Shukla, A. and Anand, S. (2016). Metric learning based automatic segmentation of patterned species. In *2016 IEEE International Conference on Image Processing (ICIP)*, pages 3982–3986. IEEE.

Singh, A., Jadoun, Y., Brar, P. S., and Kour, G. (2022). Smart technologies in livestock farming. In *Smart and sustainable food technologies*, pages 25–57. Springer.

Smisek, J., Jancosek, M., and Pajdla, T. (2013). 3d with kinect. *Consumer Depth Cameras for Computer Vision*, 17(2):3–25.

Soussi, A., Zero, E., Sacile, R., Trinchero, D., and Fossa, M. (2024). Smart sensors and smart data for precision agriculture: A review. *Sensors*, 24(8):2647.

Tasdemir, S. and Ozkan, I. A. (2019). Ann approach for estimation of cow weight depending on photogrammetric body dimensions. *International Journal of Engineering and Geosciences*, 4(1):36–44.

Terence, S., Immaculate, J., Raj, A., and Nadarajan, J. (2024). Systematic review on internet of things in smart livestock management systems. *Sustainability*, 16(10):4073.

The Pig Site (n.d.). Weighing a pig without a scale. `https://www.thepigsite.com/articles/weighing-a-pig-without-a-scale`. Accessed: 2024-12-06.

Wang, Z., Li, Q., Yu, Q., Qian, W., Gao, R., Wang, R., Wu, T., and Li, X. (2024). A review of visual estimation research on live pig weight. *Sensors*, 24(21):7093.

Witten, I. H., Holmes, G., McQueen, R. J., Smith, L. A., and Cunningham, S. J. (1993). Practical machine learning and its application to problems in agriculture.

Yan, Q., Ding, L., Wei, H., Wang, X., Jiang, C., and Degen, A. (2019). Body weight estimation of yaks using body measurements from image analysis. *Measurement*, 140:76–80.

Zhang, Z. (2012). Microsoft kinect sensor and its effect. *IEEE Multimedia*, 19(2):4–10.