3D DEPTH IMAGING FOR PIG WEIGHT ESTIMATION

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Accurate weight estimation in livestock is crucial for effective farm management, as it directly impacts feed optimization, breeding decisions, health assessment, and overall animal welfare (Wang et al., 2021). Proper weight management allows farmers to adjust feeding schedules, monitor growth, and make timely decisions that contribute to better productivity and profitability. Traditional weight measurement methods, primarily through the use of weighing scales, are labor-intensive, time-consuming, and stressful for animals, which can result in reduced productivity, increased risk of injury, and negative effects on animal welfare (Faucitano and Goumon, 2018). The high cost, operational complexity, and maintenance requirements of these weighing systems further limit their practicality, especially for small and medium-sized farms (Dickinson et al., 2013).

The primary function of telemetry systems is to collect data from sensors and transmit it to a centralized system for analysis. This process involves several key components: sensors to capture data, transmitters to send the data, receivers to collect the data, and a central processing unit to analyze and store the data. With the advent of the Internet of Things (IoT) and advancements in wireless communication technologies, telemetry has evolved significantly, enabling more efficient and comprehensive data acquisition and monitoring systems.

In aerospace, telemetry is crucial for monitoring the status and health of spacecraft and satellites, providing data on parameters such as temperature, pressure, and velocity. In healthcare, telemetry systems are used to monitor patients' vital signs remotely, allowing for timely medical interventions and reducing the need for prolonged hospital stays. Environmental telemetry systems play a pivotal role in tracking weather conditions, pollution levels, and natural disaster warnings, contributing to better disaster management and environmental protection.

The integration of telemetry in industrial applications has revolutionized how industries operate. Through real-time monitoring of machinery and processes, industries can minimize downtime, optimize performance, and enhance safety. Predictive maintenance, powered by telemetry data, allows for the identification of potential issues before they lead to failures, thereby reducing maintenance costs and improving operational efficiency.

This paper aims to explore the advancements in telemetry technology, its applications across various fields, and the future trends that could shape its development. By understanding the current state and potential of telemetry, we can better appreciate its critical role in modern technology and its impact on improving operational efficiencies and safety across different sectors.

1.2 Statement of the Problem

Accurate and efficient weight calculation in pig farming is crucial for optimizing feeding strategies, monitoring growth, and making informed management decisions (Pezzuolo et al., 2018). Proper weight monitoring directly impacts the productivity and profitability of pig farming operations as it affects key decisions such as health monitoring and determining the optimal time for the market. However, traditional methods, such as manual weighing, are often time-consuming, labor-intensive, and stressful for the animals, potentially impacting their well-being and productivity (Li et al., 2014). Manual weighing involves physically moving pigs to weighing scales which not only causes stress for the animals but also requires significant labor resources and poses safety risks for the handlers. This highlights the need for alternative approaches that are non-invasive, automated, and cost-effective.

While some investigations have explored imaging techniques for pig weight estimation, most existing studies have primarily focused on traditional monocular vision or single-camera systems (Pezzuolo et al., 2018)(Kollis et al., 2007). These systems are often limited by their inability to capture depth information accurately which is crucial for estimating body volume and weight. Furthermore, traditional imaging methods may be prone to inaccuracies due to variations in lighting conditions, pig movement, and occlusion.

Recent advancements in multi-camera systems have shown promise in improving the accuracy of livestock weight estimation (Dohmen et al., 2022). These multi-camera setups can provide more precise three-dimensional (3D) information, as a result enhancing the precision of weight estimation. Nevertheless, the complexity and cost associated with setting up and maintaining multiple cameras pose significant barriers to widespread adoption in commercial pig farming. The need for specialized equipment and significant computational ability makes such systems impractical for farmers, especially those with limited resources. Moreover, the weight of pigs and other livestock has been estimated by previous studies using a range of modeling techniques, including machine learning algorithms and linear and nonlinear functions. Although these approaches have demonstrated promise, their accuracy is frequently hampered by the quality of the input data coming from 2D photos or crude 3D reconstructions, particularly in cases when animal postures or occlusions vary.

Despite this progress made in imaging-based weight estimation, there is still a gap in the literature regarding the full utilization of Kinect's depth-sensing capabilities for weight estimation, which could offer a more practical and precise solution. Kinect cameras provide a unique opportunity to capture accurate 3D data without the need for complex multi-camera setups. It is relatively affordable, capable of capturing high-quality depth information, and easy to use, making it a practical solution for weight estimation in pig farming.

This research aims to bridge that gap by leveraging the Kinect system to capture depth image data for weight estimation in pigs. Unlike previous approaches, the Kinect-based system offers the potential to reduce reliance on complex, multi-camera setups while improving estimation accuracy. By providing detailed depth information, Kinect technology can enable more precise body volume measurements. The development of an automated, non-invasive, and cost-effective Kinect-based system could transform weight monitoring in pig farming, making it accessible even to smaller-scale farmers.

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 develop a web application for the Pig Weight Estimation System.

2. To utilize machine learning algorithms for model training and validation

to analyze depth data for pig weight estimation.

3. To assess the accuracy and efficiency of the Kinect-based pig weight estimation system in various settings.

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.

Non-Governmental Organizations. NGOs and other agricultural co-operatives can make use of the results of this study to provide support and training to farmers and livestock owners. By implementing the results in this study, cost-effective solutions based on computer vision can help improve the lives of farmers, especially in rural communities, and boost productivity in livestock farms.

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(height, posture, and lighting). The scope is limited to analyzing data collected from pigs of this specific breed, and the study will not generalize results to other pig varieties. Additionally, only pigs with a straight posture will be considered, as posture may affect the accuracy of the sensors. Pigs in other positions or with varied postures will not be considered. Environmental conditions, such as lighting and background, will be maintained as constant as possible, and while these factors may influence the sensor's accuracy, their impact will not be the subject of in-depth analysis.

The system developed in this research will employ batch processing of the collected data, meaning that real-time monitoring or continuous data acquisition is beyond the scope of this study. Instead, the data will be gathered and analyzed after the fact, limiting the immediate applicability of the system in dynamic, real-world farming environments.

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 the past, weight estimation was primarily performed manually. A common method used was Body Condition Scoring (BCS), which assesses the fatness or thinness of livestock through visual inspection and tactile assessment

(Bercovich et al., 2013). However, BCS is prone to errors and biases, as it relies heavily on the evaluator's judgment, making it less reliable.

In recent years, 3D modeling has emerged as a more accurate alternative for weight estimation. Unlike 2D images, 3D modeling captures volumetric data that correlates more precisely with the actual weight of livestock (Liu et al., 2019). The integration of 3D vision cameras with convolutional neural networks (CNNs) has further improved the accuracy and automation of weight estimation systems. CNNs excel at learning and classifying features from images, which enhances the precision of weight estimates in livestock.

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 Challenges in Weight Estimation

Weight estimation is a complex process that involves integrating multiple factors to ensure accuracy and effectiveness. In precision livestock farming, intelligent perception plays a crucial role in achieving reliable results. This includes various perception and management tasks designed to monitor and assess livestock health and performance (Bahlo et al., 2019).

One of the main challenges in livestock weight estimation is the variability in animal posture and movement. Since animals rarely maintain a consistent posture during measurement, this can lead to inaccurate assessments of their body condition. A common method for estimating an animal's fat or thinness is Body Condition Scoring (BCS), which evaluates fat reserves through visual and tactile assessments (Bercovich et al., 2013). While BCS is widely recognized for its effectiveness, it has limitations. The manual scoring process, which relies on the expertise of trained scorers, is inherently subjective and prone to inconsistency (Gjergji et al., 2020). Human judgment introduces variability and potential bias, making the results less precise. The accuracy of BCS can vary depending on the scorer's experience, perception, and environmental conditions, highlighting the need for more objective, automated methods for assessing livestock conditions.

Another challenge in weight estimation is the complexity of farm environments. These environments often lack the stable conditions necessary for accurate data collection. For example, animal features can appear differently based on posture and lighting (Ruchay et al., 2022). Inconsistent light sources can interfere with 3D imaging systems, while animal movements can shift their posture, resulting in incomplete or erroneous data.

2.3.4 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 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

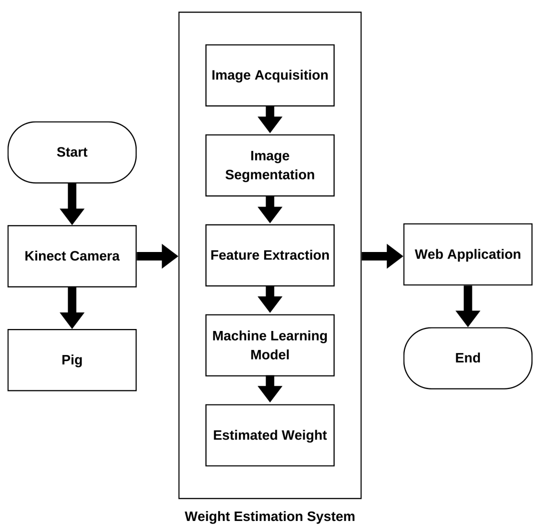

Figure 1

Figure 1 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

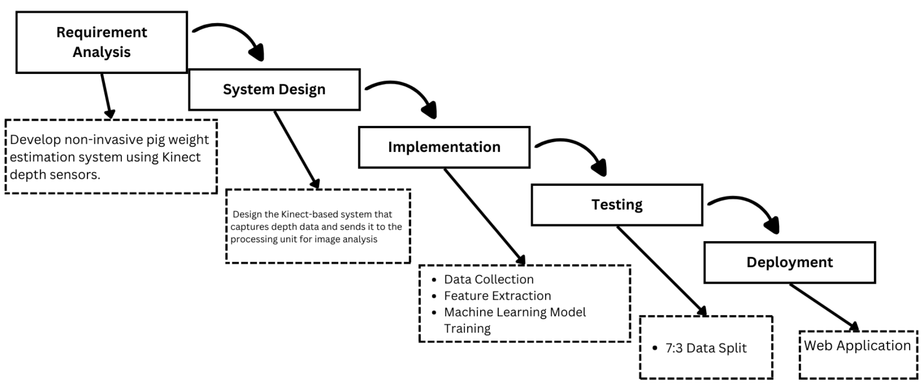

Figure 2

Figure 2 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

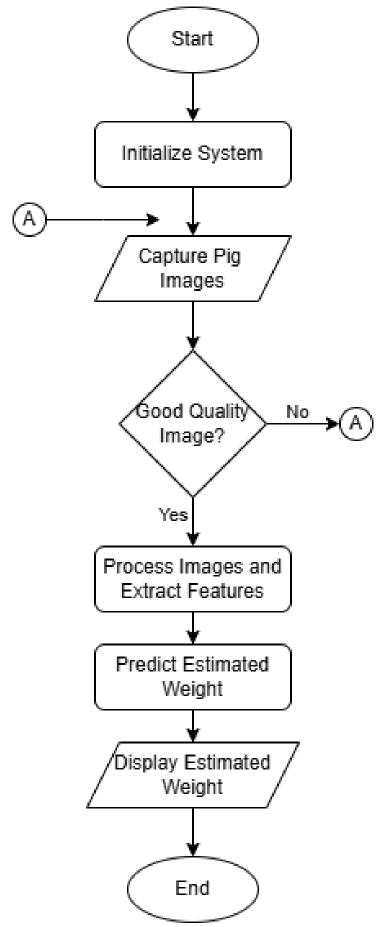

Figure 3

Figure 3 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

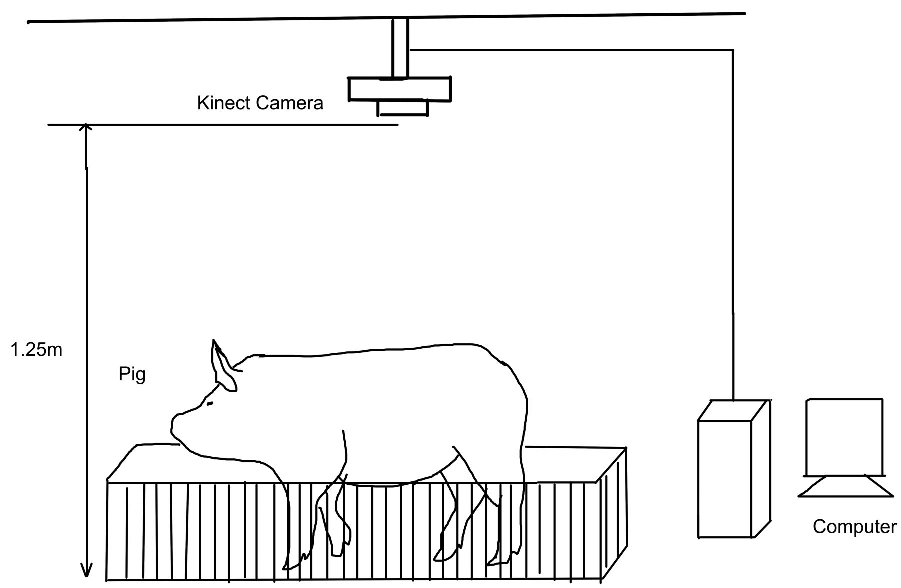

Figure 4

Figure 4 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.

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 YOLOv5 (You Only Look Once, version 5), a single-shot object detection model known for its high efficiency and accuracy in real-time applications (Bochkovskiy et al., 2020). With a CNN-based architecture, YOLOv5 processes entire images in a single pass, which optimizes speed and accuracy—key factors for agricultural use (Redmon and Farhadi, 2016; Jocher, 2021). This version was chosen over zero-shot and multi-stage detectors due to its consistent performance in detecting complex, variable shapes like animals. A pre trained YOLOv5 model, trained on Microsoft's COCO dataset, was selected to leverage transfer learning, enabling robust adaptation to pig detection without extensive retraining (Lin et al., 2014; Howard et al., 2018). By adopting this approach, we reduce training overhead and improve detection reliability, making YOLOv5 ideal for our farm setting.

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:

$$I_{\text{sharp}}(x, y) = I(x, y) + \alpha(I(x, y) - I_{\text{blur}}(x, y)) \tag{1}$$

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:

$$cX = \frac{M_{10}}{M_{00}}, \quad cY = \frac{M_{01}}{M_{00}} \tag{2}$$

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:

$$\Sigma = \frac{1}{N} \sum_{i=1}^{N} (p_i - \mu)(p_i - \mu)^T \tag{3}$$

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:

$$y_line(x) = \frac{v_y}{v_x}(x - cX) + cY \tag{4}$$

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.

$$I_{\text{filled}} = I_{\text{mask}} \oplus K \tag{5}$$

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:

$$v_i = argmax(-y(x)) \tag{6}$$

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:

$$S_region(x, y) = I_sharp(x, y)(1_[x_start, x_end]) \tag{7}$$

where S_region is the segmented region of interest.

Figure 5 shows a schematic representation of the segmentation of the pig. Following the segmentation process found in the study conducted by, the

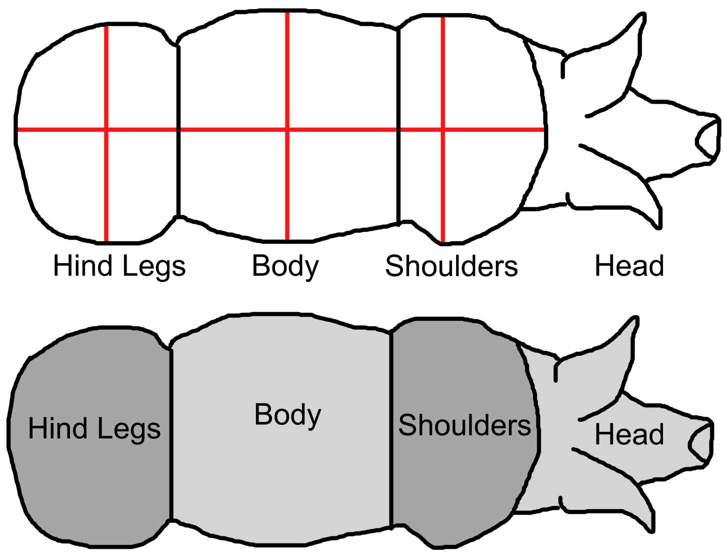

Figure 5

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:

$$x_{\text{highest}} = \max\{D(x, y) \mid (x, y) \in S(x, y)\} \tag{8}$$

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

$$y_{\text{height}} = x_{\text{highest}} - x_{\text{lowest}} \tag{10}$$

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:

$$Area = \sum_{(x,y) \in S(x,y)} 1 \tag{11}$$

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:

$$\delta(x, y) = (\frac{\partial}{\partial x}, \frac{\partial}{\partial y}) \tag{12}$$

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:

$$|\delta(x, y)| = \sqrt{\left(\frac{\partial}{\partial x}\right)^2 + \left(\frac{\partial}{\partial y}\right)^2} \tag{13}$$

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:

$$MAE = \frac{1}{N} \sum_{t=1}^{N} |\hat{y}_t - y_t| \tag{14}$$

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:

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \tag{15}$$

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

An experimental setup will be used in this study to evaluate the accuracy and efficiency of the Kinect-based pig weight estimation system. The experimental setup will involve capturing depth images of pigs in a farming environment, followed by weight estimation using machine learning algorithms. The experimental setup allows systematic data collection and evaluation to verify the system's performance compared to traditional weighing methods.

3.9 Location

The study will take place at a backyard pig-weaning farm located in El Salvador City, Misamis Oriental, Philippines. This particular farm was selected due to its favorable conditions and potential to serve as an ideal research site. To ensure reliable and consistent results, controlled conditions will be maintained throughout the study. The focus will be on Landrace pigs, which are known for their excellent growth and meat quality, with an average live weight ranging between 40 and 100 kg. This controlled environment will help ensure that any variables influencing the outcomes are carefully managed.

3.10 Equipment

The study utilizes a Microsoft Kinect V1 sensor, which will be mounted approximately 1.25 meters above the pigpen to capture a top-down view of each pig. The Kinect sensor is capable of providing depth images that are essential for measuring the pigs' physical dimensions. These depth images will be processed in real time by a computer system connected to the sensor. The system will run feature extraction algorithms designed to estimate the pigs' weight based on the data collected. To ensure accurate data capture, the pigpen will need to be free of obstructions around the pigs, as any occlusions could interfere with the depth imaging process. Additionally, consistent lighting will be maintained to reduce shadows and avoid image quality variations caused by fluctuating light conditions, both of which are crucial for producing reliable data. By addressing these factors, the study aims to provide precise and consistent measurements throughout the observation period.

3.11 Data Collection

The Kinect sensor will be positioned to capture depth images of each pig. Multiple images of each pig will be taken to account for posture variation. The system will discard low-quality images through an automatic image quality check. Using the captured images, the system will extract features such as body height, surface area, and volume from the depth data. These features will then be put into a pre-trained machine-learning model for weight estimation.. The Kinect sensor will be calibrated before the start of the data collection to ensure that the depth measurements are accurate and to compensate for the different lighting in the environment and the distance between the ground and the Kinect sensor. A reference weight for each pug will be recorded using a traditional weighing scale, which will use the accuracy of the Kinect-based system. The estimated weight from the depth images will be calculated automatically using the machine learning model through the system, which was trained using previously available data sets. The estimated values would then be compared to the reference weight values collected manually to assess the system's accuracy.

3.12 Verification

The verification process will involve comparing the weights estimated by the Kinect-based system with the actual weights recorded by the traditional weighing scale. A statistical analysis will be conducted where the Mean Absolute Error and the Root Mean Square Error will be calculated between the estimated and actual weights to quantify the system's accuracy. Cross-validation will be done using a Test-Train split. The data set will be split into a 70 percent training set and a 30 percent testing set to ensure that the system is not overfitting and can generalize to new pigs. Different Machine learning models will then be tested to select the model with the best performance.

APPENDICES

Type your appendix here.

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