ERIA Research Project Report FY2025, No. 36

The Role of AI-Powered Mobile Apps in Cattle Weight Estimation

Economic Research Institute for ASEAN and East Asia

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ERIA Research Project Report FY2025, No. 36
Published in December 2025

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Chapter 1
Introduction

1. Background

The livestock industry represents a vital pillar of Malaysia's agricultural sector, contributing significantly to the national economy, food security, and rural community development. According to the Malaysian Green Technology and Climate Change Centre (2023), the poultry sub-sector contributes 98.9% and the dairy sub-sector 64.19% to the livestock sector of Malaysia's agricultural GDP. Cattle farming, in particular, plays a crucial role in ensuring domestic beef supply, although Malaysia continues to import a substantial portion of beef to meet growing demand.

As Malaysia's population surpasses 33 million (Department of Statistics Malaysia, 2025b) and urbanisation intensifies, there is increasing pressure on the livestock industry to enhance productivity, maintain consistent quality, and meet consumer expectations for ethically sourced, sustainable animal products. These developments make improvements in livestock management critical to addressing challenges related to resource limitations, market competitiveness, and environmental sustainability. Central to effective livestock management is the accurate estimation of cattle weight, which underpins growth monitoring, health assessments, feed optimisation, breeding decisions, and market transactions (Baris, 2023; Zhao, 2023; Hossain et al., 2025).

Traditionally, cattle weighing has relied on mechanical or electronic scales, which, while accurate under controlled conditions, present numerous operational and financial challenges (Tscharke and Banhazi, 2013). These methods are labour-intensive, often requiring multiple workers to handle and restrain animals, inducing stress, compromising welfare, and potentially affecting growth and meat quality. Furthermore, the upfront cost of commercial weighing systems – ranging from several thousand to tens of thousands of ringgit depending on capacity and features – along with maintenance and calibration requirements, imposes a substantial financial burden, particularly for smallholder farmers who constitute a large portion of Malaysia's livestock producers. Accessibility issues, including difficult terrain, transportation constraints, and the lack of specialised facilities in rural areas, further limit the feasibility and efficiency of conventional weighing practices. Empirical studies highlight that labour and operational inputs significantly drive production costs, making labour-intensive weighing workflows a major economic challenge for smallholders.

The rapid evolution of artificial intelligence (AI) technologies and mobile devices presents a timely opportunity to address these longstanding challenges in livestock management (Kırbaş, 2025; Xu et al., 2024). AI-based mobile applications for cattle weight estimation can reduce reliance on manual handling, lower operational costs, improve accuracy, and enhance animal welfare. Given the critical role of livestock in Malaysia's agricultural economy, the challenges inherent in traditional weighing practices – including labour intensity, high operational costs, limited accessibility, and welfare concerns – underscore the need for innovative solutions. Accurate weight estimation is essential not only for growth monitoring, health assessment, and feed optimisation but also for supporting informed breeding and market decisions.

Investigating the potential of AI-based cattle weight management is therefore highly relevant, as such systems can enhance productivity, reduce operational burdens for smallholder farmers, improve animal welfare, and contribute to broader efforts toward digitalising Malaysia's livestock industry, while offering a scalable model for adoption across the ASEAN region. This study focuses on evaluating the practical applicability, challenges, and opportunities of such AI-based solutions within Malaysia's specific agricultural context, with implications for broader adoption across ASEAN nations.

2. Research Objectives and Scope

Recognising the potential of AI technologies in revolutionising livestock management, this study was initiated to assess the feasibility, accuracy, economic viability, and scalability of AI-based mobile applications for cattle weight estimation in Malaysia. The study was conducted in collaboration with the Economic Research Institute for ASEAN and East Asia (ERIA) under the One ASEAN Startup Award initiative, which seeks to promote technological innovation across the region.

This study aimed to:

- Evaluate the technical performance of AI weight estimation models compared to conventional methods.
- Identify the operational and financial benefits and challenges associated with AI adoption for farmers.
- Explore strategies to support widespread technology adoption across various scales of cattle farming operations in Malaysia and the broader ASEAN region.

3. Significance of the Study

This study is significant for several reasons. First, it aligns with Malaysia's national agenda for agricultural digitalisation and modernisation, contributing to both food security and economic resilience. Second, it empowers smallholder farmers by providing affordable and user-friendly technological tools that can enhance productivity and profitability. Third, the study promotes humane livestock management practices by reducing stress and physical intervention during weight assessments, thereby improving animal welfare. Moreover, it offers insights and policy recommendations that can inform government programmes, subsidies, and regulatory frameworks aimed at supporting digital agriculture. Finally, the study has the potential to serve as a scalable model for other ASEAN countries confronting similar challenges in livestock management.

3.1. Institutional Collaboration with the Department of Veterinary Services Malaysia

To further enhance the scientific rigour and practical relevance of this study, IPINFRA Networks has initiated a formal collaboration with DVS Malaysia. This collaboration facilitates the alignment of the AI-based cattle weight estimation technology with national livestock management standards, regulatory frameworks, and animal welfare guidelines. Through the active involvement of DVS, the research benefits from institutional support, ensuring that the proposed technological solutions are both operationally feasible and policy-compliant. Such collaboration is instrumental in promoting wider acceptance, fostering regulatory endorsement, and supporting the potential nationwide deployment of AI innovations within Malaysia's livestock sector.

4. Structure of the Report

Following this introduction, Chapter 2 describes the background of the study and technological underpinnings of AI in livestock management. Chapter 3 outlines the research objectives and research questions guiding the study. Chapter 4 provides a comprehensive literature review on traditional and AI-based cattle weight estimation methods. Chapter 5 details the research methodology employed in the study. Chapter 6 presents the research findings, including a comparative analysis and feasibility assessments. Chapter 7 proposes policy recommendations for facilitating AI adoption in livestock management. Chapter 8 concludes the study and outlines future research directions.

Chapter 2
Literature Review

The literature on livestock management, AI, and digital agriculture has expanded considerably over the past decade, reflecting growing interest in the potential of emerging technologies to improve productivity, efficiency, and sustainability. This chapter reviews existing studies on traditional cattle weighing methods, the development and application of AI-based solutions, particularly CNNs for weight estimation, and the key challenges that influence the adoption of such technologies in practical farming contexts.

1. Technological Innovations in Livestock Management

Traditional cattle weighing practices have long been fundamental to livestock management. Farmers typically employ mechanical or electronic scales to measure animal body weight – an essential metric for monitoring growth, determining market readiness, optimising feeding strategies, and assessing health conditions However, extensive research indicates significant limitations associated with these methods. Manual weighing requires multiple workers to restrain and guide animals onto weighing platforms, leading to high labour costs and an increased risk of worker injury (Tscharke and Banhazi, 2013; Wilgenbusch, 2022). The effects of stocking density and transport distances in Brahman cross-bred cattle in Malaysia revealed increased cortisol and EEG-based stress markers under more severe handling or confinement conditions, confirming that such practices adversely affect behaviour, physiology, and welfare (Abubakar et al., 2021). Studies also found that the high initial cost of weighing equipment, combined with ongoing expenses for maintenance and calibration, restrict access for smallholder farmers, especially in rural areas. Manual weighing procedures also diminish operational efficiency, as they are time-consuming, particularly for large herds. These limitations underscore the need for innovative, less intrusive, and more cost-effective solutions for cattle weight monitoring.

Recent advancements in digital agriculture, particularly in AI, have opened transformative opportunities to overcome traditional livestock management challenges. AI, combined with machine learning (ML) and mobile technologies, offers innovative and scalable solutions to enhance agricultural productivity, operational efficiency, and animal welfare (Kırbaş, 2025; Xu et al., 2024). Globally, AI applications in agriculture – often termed 'smart farming' or 'precision livestock farming' – are increasingly deployed in areas such as automated animal monitoring, disease detection, predictive breeding analytics, and image-based weight estimation (Menezes, 2025). Key components of the smart farming or precision livestock farming could include:

1) Convolutional Neural Networks (CNNs): a key AI tool that has demonstrated exceptional potential in analysing visual data to accurately estimate livestock body condition scores and weights, enabling data-driven management decisions. CNNs are used to extract relevant features (e.g. body width, height, body length) from images and correlate them with weight data.

   In this case, CNNs have become the backbone of modern image-based livestock monitoring systems due to their ability to automatically learn and extract hierarchical features from images without manual intervention. Existing studies highlight CNNs' strengths, such as high accuracy, adaptability, and scalability. CNNs can capture complex spatial relationships and body contours, leading to highly accurate weight predictions (Wang et al., 2020). As for adaptability, transfer learning allows CNN models trained on general datasets to be be fine-tuned for specific cattle breeds and local conditions, hence improving performance with relatively smaller datasets (Rahman et al., 2018). These models, once trained, can be scaled up for deployment on mobile devices, allowing for real-time processing without the need for powerful servers. Despite these advantages, model accuracy can still be influenced by environmental variability (e.g. lighting and background clutter), cattle pose (e.g. side vs. front view), and camera quality.

2) ML Regression Models: Employed to refine the relationship between extracted features and actual cattle weight.

3) Smartphone Integration: Offers portability, affordability, and ease of use, enabling farmers to conduct weight estimation independently without specialised equipment.

The integration of AI technologies into livestock management presents a promising avenue to overcome the limitations of traditional weighing methods. In particular, image processing techniques combined with ML algorithms enable non-invasive, rapid, and accurate estimation of cattle body weight. Key developments include the application of computer vision and deep learning, particularly using CNNs, to analyse livestock body dimensions from 2D images (Rohan et al., 2024). Automated weight estimation is achieved by extracting features such as body width, length, and girth from images, which ML models use to predict cattle weight with high precision, hence eliminating the need for physical weighing (Wang et al., 2020).

By leveraging smartphone cameras and AI algorithm, these applications eliminate the need for physical scales and extensive human handling, offering a fast, non-invasive, and precise solution. This reduces labour requirements, minimises animal stress and injury, and enables farmers to make informed, data-driven decisions for growth monitoring, feed optimisation, and breeding management. Beyond operational benefits, AI-driven weight estimation contributes to broader sustainability goals by improving livestock productivity, optimising resource use, and reducing the environmental footprint of farming practices, positioning AI as a critical enabler of Malaysia's digital livestock transformation.

2. Global and Regional Trends in IoT and AI in Livestock Farming

Globally, the livestock industry is undergoing a digital transformation driven by AI, the Internet of Things (IoT), and big data analytics. Smart farming technologies now enable real-time monitoring, disease detection, predictive analytics, and non-invasive biometric measurements (Menezes, 2025). Within the Asia-Pacific region, countries such as Australia, Japan, and Thailand are rapidly integrating AI solutions into their livestock sectors (Vlaicu et al., 2024; Ohashi, 2024; Eckhardt, 2025). Indonesia is also emerging as a critical frontier for smart farming, supported by its large agricultural base and government-led initiatives such as the '100 Smart Cities' programme and smart village projects (Susilowati, 2025). These regional developments illustrate how AI adoption is becoming central to modernising livestock management and addressing operational challenges.

At the regional level, the deployment of AI-based cattle weight estimation technologies advances ASEAN's broader sustainability and innovation agenda. ASEAN guidelines on promoting the utilisation of digital technologies for ASEAN food and agricultural sector (ASEAN, ERIA, and SEARCA, 2021) emphasise the role of smart farming technologies in enhancing productivity, resilience, and sustainability across member states. These technologies also align with two Sustainable Development Goals (SDGs), namely SDG 2 (Zero Hunger) and SDG 12 (Responsible Consumption and Production) by supporting food security, encouraging responsible production, and creating economic opportunities for rural communities. By facilitating technological inclusivity, AI solutions can help narrow the digital divide between large commercial farms and smallholder operations, ensuring that innovation benefits all levels of the agricultural sector.

Building on this broader digital transformation, integrating AI-powered cattle weight estimation into farm management systems offers specific and practical benefits for farmers. Automated weight measurements enable continuous, data-driven monitoring of livestock growth, early detection of health issues, and optimisation of feeding strategies (Kırbaş, 2025; Xu et al., 2024). Predictive analytics can further forecast weight gain trajectories, improve breeding programme outcomes, and inform marketing strategies. In addition, AI integration enhances traceability and regulatory compliance by automating data collection, ensuring adherence to quality standards, and supporting animal welfare and food safety regulations. By combining AI algorithms with cloud-based platforms, IoT-enabled sensors, and mobile applications, cattle weight estimation can form a key component of a comprehensive digital ecosystem, empowering farmers with actionable insights to improve productivity, animal welfare, and overall operational efficiency.

3. Livestock Market Dynamics and AI Adoption Potential in Malaysia and Indonesia

Malaysia and Indonesia collectively represent a substantial livestock market opportunity in Southeast Asia. In Malaysia, the poultry sub-sector contributes 98.9% and the dairy sub-sector 64.19% to the livestock sector of agricultural GDP, yet the country still imports over 70% of its beef demand, indicating significant untapped local production capacity (Abu Dardak, 2025; Mohamed, Hosseini, and Kamarulzaman, 2013). Based on data from Malaysia's Department of Veterinary Services, Zayadi (2021) notes that ruminant livestock producers such as cattle are mostly smallholder farmers in Malaysia, in contrast to commercial non-ruminant sectors, and those smallholder farmers often face financial constraints and limited access to advanced technologies. Cost-effective, mobile-based AI solutions can address these challenges by improving livestock management practices, enhancing productivity, and increasing market competitiveness. By narrowing the technology gap between rural and urban farming communities, such tools also promote rural development and support sustainable agriculture through precise feeding, health monitoring, and growth tracking, optimising resource use while minimising environmental impact. Malaysia's *National Agrofood Policy 2021–2030* further underscores the importance of digital agriculture adoption, highlighting AI-based cattle weight estimation technologies as a strategic contributor to sector modernisation (Ministry of Agriculture and Food Industries, 2021).

Understanding the importance of digital agriculture adoption, in Malaysia, AI is gradually being integrated into agriculture through initiatives like the *National Agrofood Policy* and smart farming grants from the Ministry of Agriculture and Food Security. Yet, adoption amongst small and medium-scale livestock farmers remains limited due to technological unfamiliarity, infrastructure gaps, and cost concerns. AI-powered mobile applications for cattle weight estimation address these barriers by using smartphone cameras to capture images, which are then processed through AI algorithms to estimate weight based on body dimensions, shape analysis, and visual markers. These systems combine CNNs for feature extraction, ML regression models for weight prediction, and mobile integration for accessibility, affordability, and ease of use.

Meanwhile, In Indonesia, one of the world's top ten largest beef-consuming countries, there is a strong national agenda to reduce dependency on beef imports by enhancing domestic cattle production. The country is home to over 10 million–12 million cattle and buffaloes, creating a substantial opportunity for technological interventions that enhance productivity and animal welfare (Musa, 2025). Therefore, the expansion of IPINFRA Networks, a Malaysia-based startup offering AI-powered cattle weighing applications, is therefore driven by this market potential and the regional synergies achievable through scalable digital agriculture tools. Deploying AI-based livestock solutions in Indonesia can improve decision-making, reduce operational inefficiencies, and foster more sustainable, data-driven livestock production.

4. Challenges in Implementing AI-Based Solutions in Agriculture

While AI-powered cattle weight estimation technologies hold significant promise, several challenges must be addressed to ensure their successful adoption. First, environmental variability – including differing lighting conditions, shadows, animal postures, and cluttered farm settings – can affect the quality of captured images and, consequently, the accuracy of AI predictions (Araújo et al., 2025). Robust model training with diverse datasets is essential to account for these real-world conditions. Second, technological limitations present barriers: not all farmers possess high-end smartphones with adequate camera capabilities, and connectivity remains inconsistent (Department of Statistics Malaysia, 2025a). Drive-test studies in rural Johor, Sabah, and Sarawak show substantial variability in 4G network performance, while qualitative studies amongst smallholders highlight poor access to and dissatisfaction with ICT infrastructure (Shayea et al., 2020; Omar et al., 2024). These factors can impede cloud-based AI processing and real-time data synchronisation. Thirdly, farmers' digital literacy is a critical factor, as familiarity and comfort with digital tools directly influence the effective use of AI applications. Targeted training and educational initiatives are therefore essential to bridge knowledge gaps and build user confidence, enabling smallholders to fully benefit from AI-based livestock management solutions (Rahman et al., 2018).

4.1. Regulatory Challenges in Personal Data Protection (PDP) in Malaysia and Indonesia

As digital agriculture expands, several ethical issues arise regarding data ownership, usage, sharing, and the protection of farmers' privacy. Studies indicate that many contracts between farmers and technology providers grant substantial control over farm data to providers, often without farmers fully understanding the implications (Mark, 2019). Security risks – including unauthorised access through sensors, data breaches, and misuse of collected information – further complicate the responsible deployment of AI and IoT technologies in agriculture. Ethical frameworks proposed by Dara, Hazrati Fard, and Kaur (2022) emphasise key principles such as transparency (ensuring farmer consent and control over data), accountability (clear responsibility for adverse outcomes), fairness (avoiding bias), and privacy (protecting personally identifiable information). Reviews of big data in agriculture also highlight an urgent need for clarity over ownership, particularly when data originate from heterogeneous sources including researchers, private technology firms, and public institutions (Sapienza, 2021).

In the Malaysian context, the World Bank (2024) underscores that robust policy frameworks for data governance, security, and privacy are essential to build trust and enable fair access to technology benefits amongst rural stakeholders. A key driver of this study is the contrasting regulatory landscapes in Malaysia and Indonesia regarding personal data protection (PDP). Malaysia's Personal Data Protection Act (PDPA) 2010 is relatively mature, offering clear guidance for entities handling personal or sensitive information, including data generated by smart agriculture applications. Conversely, Indonesia's PDP Law (Law No. 27/2022) remains in the early stages of implementation, creating uncertainties for tech startups and foreign enterprises regarding compliance expectations (Budiman, 2023). These differences present challenges in cross-border data transfers, AI model training using farm-level data, and the management of user consent. This study by IPINFRA aims to examine these disparities, inform compliance strategies, and propose policy frameworks that could harmonise PDP regulations across ASEAN, thereby supporting responsible, ethical, and equitable adoption of AI in livestock management.

Chapter 3
Research Methodology

1. Data Collection

Accurate data collection is crucial for training and validating AI models to ensure reliable weight prediction. This process involved three key steps: capturing high-resolution cattle images, performing traditional weight measurements to establishing ground truth, and documenting environmental variables as well as other metadata.

The research team utilised high-resolution cameras with varying focal lengths to capture cattle from multiple angles, including front, side, and rear views. For each image, the photographs were taken at a resolution sufficient to capture fine anatomical details. In the process of taking the photographs, it was paramount to ensure consistent lighting conditions and a stable camera placement to minimise variability in image quality. Multiple cameras were positioned around each animal, and drones were used for aerial shots to provide comprehensive coverage in a single session. Images were collected across different postures and environments (e.g. grazing, standing still, or walking) to enhance the model's robustness.

For weight measurements, an industrial-grade scale was employed to obtain accurate and consistent readings, which served as the ground truth to be compared with the AI model's predictions. Weights were recorded at regular intervals (e.g. weekly) to track changes over time, with corresponding images paired to create labelled training data. For consistency, the team used a standardised method of weighing across all animals to minimise bias, ensuring measurements were taken under consistent conditions (e.g. same time of day).

The third step involved documenting relevant contextual data. Environmental variables consisted of a) breed, as certain breeds may exhibit different growth patterns and body shapes; b) age and sex, which are key factors influencing cattle growth; and c) feeding history, as nutritional intake is known to have a direct impact on weight and body composition. Additional metadata – such as health conditions, medication history, and environmental factors (e.g. temperature and humidity) – were included as these can also influence weight.

2. AI Model Development

The AI model was developed using deep learning techniques to predict cattle weight from the images captured. The process consisted of four key steps:

1) Training Deep Learning Models (CNNs) on Collected Data

The collected images were preprocessed by resizing, normalising, and augmenting the dataset. This included random cropping, flipping, and rotating images to simulate different cattle poses. CNN architectures – such as ResNet, VGGNet, or EfficientNet – were selected to extract features from the images, as CNNs are particularly effective in recognising patterns in image data The next step involved defining a loss function (e.g. Mean Squared Error) to evaluate the deviation of predicted weights from the ground truth, which in turn directed the model's learning process.

2) Applying Transfer Learning to Enhance Performance

Pretrained CNNs (e.g. models trained on ImageNet) were fine-tuned with the collected cattle image dataset to utilise the previously learned features from large datasets while adapting to the specific characteristics of the cattle body. Layer adjustments were made to improve prediction accuracy, focusing on higher-level features that correlated with cattle body mass.

3) Implementing Hyperparameter Tuning and Error Analysis

Model performance was optimised by experimenting with different hyperparameters (e.g. learning rate, batch size, and optimiser type). This process required a systematic approach, such as grid search or random search, to explore combinations. Additionally, model errors were analysed by reviewing false predictions to understand where the model performed poorly (e.g. certain breeds, ages, or lighting conditions). The results helped the research team in deciding whether to pursue model refinements or expand the dataset.

4) Optimising Models for Real-Time Mobile Device Processing

To enable deployment on mobile devices with limited processing power, the model was compressed using techniques such as pruning, quantisation, and knowledge distillation. The final optimised model was tested for real-time performance, allowing farmers to obtain instant weight estimations from captured images.

3. Field Testing

Field testing was conducted to evaluate the model's performance under real-world conditions and to gather feedback from end-users (farmers).

1) Conducting Pilot Studies Comparing AI-Based and Traditional Methods

Pilot tests on different farms were carried out using both AI-based methods (image-based weight prediction) and traditional weighing (scales). This provided a comparative basis for evaluating the accuracy, time, and cost benefits of using AI. The AI model was tested across varying environmental conditions – including different lighting and weather conditions and farm settings – to assess its robustness and usability.

2) Gathering Farmer Feedback on Usability, Reliability, and Improvements

Interviews and surveys with farmers were conducted to understand their experiences with the AI-based system, focusing on usability (ease of use and time savings), reliability (accuracy of predictions), and overall satisfaction. The research team also observed how farmers interacted with the mobile applications to identify any usability issues (e.g. interface design, ease of navigation, and error handling).

4. Comparative Analysis

A rigorous analysis was conducted to compare the AI model's performance with traditional weight measurement techniques.

1) Analysing Statistical Accuracy Using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE)

Model accuracy was assessed by calculating the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) between AI-generated weight predictions and traditional measurements. The team then performed statistical tests (e.g. t-tests) to determine if the difference between the two methods was statistically significant.

2) Assessing Time and Cost Efficiency

Measuring the time taken for traditional weighing versus AI-based weight prediction was also necessary, as this helped quantify potential time-saving benefits of using AI in the field. This was followed by a cost comparison, accounting for AI-related equipment (e.g. cameras and mobile devices) versus traditional systems – which involved scales and labour costs – to assess the financial viability of adopting AI-based systems on farms.

5. Scalability Assessment

Scalability testing ensures that the AI system can be used across farms of varying sizes and conditions.

1) Testing Performance Across Different Farm Sizes and Environments

The research team tested the model's performance on small, medium-sized, and large farms, assessing its ability to adapt to different herd sizes and types of infrastructure (e.g. open pastures vs. confined pens). Environmental factors – such as varying levels of lighting, dust, and humidity – were also considered to determine whether they affected the model's accuracy.

2) Identifying Infrastructure Requirements for Broad Adoption

Another key step was to determine the minimum hardware specifications for mobile devices, cameras, and servers required to deploy the AI system across farms. The same assessment was applied to software and network requirements, with the aim of ensuring that the AI model could be scaled and remain accessible in rural or remote farming areas.

Chapter 4
Research Findings

1. Traditional Methods vs. AI-Based Approach

This section compares traditional cattle weighing methods with the AI-based weight estimation approach, focusing on key aspects such as time efficiency, animal stress, accuracy, equipment costs, labour requirements, and accessibility. Table 4.1 provides a detailed comparison.

Table 4.1. Comparison Between Traditional and AI-Based Cattle Weighing Methods

Aspect	Traditional Weighing	AI-Based Estimation
Time Efficiency	10–15 minutes per animal	Seconds per image
Animal Stress	High (due to the handling process, movement, and waiting)	Low (AI-based estimation can be done passively without disturbing the animal)
Accuracy	±5%–10% deviation (due to human error, scale calibration issues, and inconsistent animal positioning)	±2%–3% deviation (AI model trained on consistent data from multiple angles, ensuring more accurate predictions)
Equipment Costs	RM5,000–RM20,000 (US$1,186–US$4,742) for industrial-grade scales, transportation, and infrastructure	RM1,000–RM4,000 for a smartphone with a camera
Labour Requirement	2–3 workers (to assist with handling the animal, operating the scale, and recording measurements)	1 worker (can take images and process them on a mobile device, reducing workforce needs)
Accessibility	Limited (requires specialised equipment and space to set up scales, often not feasible in remote or large pastures)	High (smartphones and cameras can be used in various environments, including remote farms, with minimal infrastructure)

Source: Author’s data, 2025.

1.1. Analysis of Findings

The following analysis examines the comparison between traditional weighing methods and AI-based estimation, structured around the aspects presented in Table 4.1.

1) Time Efficiency

The traditional weighing process involves capturing the animal, ensuring it stands still on the scale, recording the weight, and sometimes repeating the process for accuracy. This can take 10–15 minutes per animal, especially on farms with limited infrastructure or uncooperative animals. In contrast, the AI-based system can estimate an animal's weight within seconds by analysing a few high-resolution photos taken from different angles, processing the data in real time. This streamlined approach is considerably faster and more efficient.

2) Animal Stress

Traditional methods require physical handling of the animal, which can cause stress due to confinement in small spaces or movement restrictions. This is especially true for larger, more aggressive animals. The AI system, by contrast, uses cameras or drones, allowing farmers to capture images from a distance without physical interaction with the cattle. This results in minimal stress for the animals, as they remain undisturbed.

3) Accuracy

Traditional methods can produce deviations of ±5%–10% due to several factors, such as improper scale calibration, inaccurate readings, or inconsistent animal positioning. These errors can accumulate over repeated measurements, reducing the system's reliability. AI models trained on large datasets of cattle images can achieve considerably higher accuracy, typically within a ±2%–3% deviation. Moreover, deep learning models can recognise and account for subtle features that affect body mass, leading to more precise estimations.

4) Equipment Costs

The initial cost for traditional cattle weighing equipment, such as industrial-grade scales and infrastructure (e.g. weighing pens), can range from RM5,000 to RM20,000, depending on the scale's complexity and size. Additional maintenance and operational costs also apply. In comparison, an AI-based solution requires only a smartphone with a high-resolution camera, costing between RM1,000 and RM4,000. This makes the AI-based system far more cost-effective, particularly for small to medium-sized farms.

5) Labour Requirement

The manual cattle weighing method often requires two to three workers – one to handle the animal, another to operate the scale, and possibly a third to record the data. In more labour-intensive settings, even more workers may be needed. With the AI system, only a single worker is necessary to capture images using a smartphone or camera, significantly reducing the labour demand and making the process more streamlined and efficient.

6) Accessibility

Traditional methods are less accessible as they rely on heavy equipment such as scales, pens, and sometimes transportation for the cattle. In remote areas or farms with large pasturelands, this can be cumbersome and impractical. One of the strongest advantages of AI-based systems is their portability; smartphones and cameras can be used in almost any environment, making the technology highly accessible for farmers in rural or hard-to-reach areas. Additionally, AI systems can be easily scaled up for use across different farms.

In conclusion, the AI-based estimation approach demonstrates significant advantages over traditional cattle weighing methods, particularly in terms of time efficiency, accuracy, cost, and labour requirements. The reduced stress on animals, coupled with the lower cost and higher accuracy, makes the AI-based system a compelling alternative, especially for farmers looking to improve operational efficiency while minimising disruptions to their animals. The scalability and accessibility of the AI solution further support its potential for widespread adoption in diverse farming environments.

2. Challenges and Opportunities

Despite the strengths of AI-powered cattle weighing applications, certain challenges may hinder adoption. From a technical perspective, these applications require large datasets to ensure accuracy, and these datasets need to be updated regularly, considering that environmental factors can influence performance. On the user side, farmers may lack familiarity with AI technologies, and variations in smartphone quality can reduce the apps' effectiveness on certain devices. Internet connectivity is a similar issue, as it depends on both the device and whether the farm is located within a mobile provider's coverage area. Furthermore, although AI solutions are generally cost-effective, the initial integration of such technology into devices can still incur costs that may be prohibitive for some farmers.

With challenges come opportunities for long-term efficiency gains. While the upfront costs of AI adoption may be high, the technology has the potential to reduce operational expenses in the long run. Government incentives supporting smart agriculture can help offset adoption costs, and the scalability of AI systems offers further advantages. This scalability applies both geographically – enabling replication across ASEAN countries beyond Malaysia – and functionally, by enhancing livestock supply chain traceability in the future. Furthermore, integrating AI into IoT-based farm management systems could provide a more holistic approach to farm management.

3. Comparative Analysis of PDP Regulations: Malaysia vs. Indonesia

Discussing the comparative analysis of personal data protection (PDP) regulations in Malaysia and Indonesia is critical for this study because AI-based cattle weight management tools rely on the collection, storage, and processing of farm-level data, which often include personally identifiable information of farmers and sensitive operational details. The regulatory landscape directly affects how these technologies can be deployed, shared, and scaled across borders. Understanding these regulatory differences is essential for ensuring legal compliance, safeguarding farmer data, and fostering trust in AI applications. Moreover, it informs strategies for cross-border deployment, model training using heterogeneous datasets, and the development of policy recommendations that could harmonise PDP practices across ASEAN, ultimately supporting the ethical, responsible, and scalable adoption of AI-driven livestock management technologies.

3.1. Legal Framework Overview

Before examining the specific regulatory environments of Malaysia and Indonesia, it is important to understand the broader context of personal data protection (PDP) in the ASEAN region. PDP laws establish the legal basis for how personal, sensitive, and operational data can be collected, processed, stored, and shared. These frameworks are particularly relevant for AI-powered livestock management tools, such as cattle weight estimation applications, which rely on capturing farm-level data and, in some cases, information linked to individual farmers. A clear understanding of the legal landscape is essential not only for ensuring compliance and safeguarding user privacy, but also for facilitating trust, cross-border deployment, and responsible data-driven innovation in the agricultural sector. Below is an overview of the personal data protection (PDP) legal frameworks in Malaysia and Indonesia.

3.1.1. Malaysia

Malaysia enacted the Personal Data Protection Act (PDPA) 2010, making it one of the earliest ASEAN members to legislate data privacy. Administered by the Department of Personal Data Protection (JPDP), the PDPA applies to commercial transactions involving personal data. Although agriculture is not explicitly addressed, digital agriculture tools –

especially those involving user accounts or image capture – fall under its purview when used by commercial farming enterprises.

3.1.2. Indonesia

Indonesia's Law No. 27/2022 on Personal Data Protection is modeled after the European Union's General Data Protection Regulation (GDPR). The law mandates lawful, fair, and transparent data processing and applies to both private and public entities. Enforcement will be led by a forthcoming Data Protection Authority, expected to become operational by 2024–2025. The regulation is still being implemented in phases, creating a period of legal ambiguity for tech startups operating in the country.

3.2. Definition of Personal Data

Table 4.2 provides a comparative overview of how personal data is defined under Malaysia's PDPA 2010 and Indonesia's PDP Law 2022. Understanding these definitions is essential for AI-based livestock management applications, as they determine what types of data require legal protection and consent from individuals.

Table 4.2. Definition of Personal Data in Malaysia and Indonesia

Element	Malaysia (PDPA 2010)	Indonesia (PDP Law 2022)
Personal Data	Any data that identifies an individual	Any data that directly or indirectly identifies an individual
Sensitive Personal Data	Includes health data, religion, political opinions, etc.	Includes health, biometric, and genetic data, and sexual orientation
Livestock Data Relevance	Not classified as personal data unless tied to individuals	If linked to identifiable farmers or farm owners, it may fall under PDP law

Source: Author's data, 2025.

In Malaysia, personal data is broadly defined as any information that identifies an individual, while Indonesia's law extends this to data that directly or indirectly identifies a person. Both frameworks recognise sensitive personal data, such as health information; however, Indonesia explicitly includes biometric, genetic data, and sexual orientation as sensitive categories, reflecting a slightly broader scope. Regarding livestock-related data, Malaysia does not classify such information as personal unless it can be linked to specific individuals. In contrast, Indonesia's regulations indicate that livestock data associated with identifiable farmers or farm owners may fall under PDP provisions.

This comparison underscores the importance of carefully assessing how AI tools capture, process, and store farm-level data in each country. Compliance with these definitions ensures that developers and operators of digital livestock management systems protect individual privacy, secure informed consent, and mitigate legal risks, particularly in cross-border deployments across ASEAN.

3.3. Consent Mechanisms

Both Malaysia and Indonesia emphasise informed consent as a legal basis for processing personal data. Malaysia requires explicit consent prior to data collection, with clear explanations of the purpose and retention period. Similarly, Indonesia mandates explicit and informed consent, including provisions for withdrawal and rectification, reflecting a GDPR-like approach. For agritech and livestock-related companies like IPINFRA, these requirements are particularly relevant when collecting data from farmers or livestock owners via mobile apps or IoT devices. Consent forms must be multilingual, transparent, and easily accessible, especially for rural users or those with limited literacy, ensuring that personal and farm-related data (e.g. herd health records, breeding information) are handled ethically and legally.

3.4. Cross-Border Data Transfer Restrictions

Malaysia restricts data transfers to countries that do not provide an ‘adequate’ level of protection, requiring either consent or ministerial approval. Indonesia similarly requires data controllers to ensure foreign jurisdictions provide equal or stronger protection and mandates reporting of transfers to regulators. For AI-driven agriculture and livestock platforms, these rules are critical. Startups aiming to expand their solutions – such as precision farming, crop monitoring, or herd management tools – across borders must navigate these legal requirements to enable real-time data processing, cloud-based analytics, and remote monitoring.

For instance, IPINFRA’s AI-powered cattle weight management system faces similar considerations. Expanding operations to other countries in ASEAN requires careful planning to ensure cross-border data flows comply with local regulations. Without harmonised frameworks or mutual recognition agreements, the platform may experience delays or limitations in tracking herd weights, feeding patterns, and health metrics, which could affect predictive analytics and operational efficiency. By proactively addressing these legal constraints, IPINFRA and other agritech startups can better position themselves for seamless regional expansion.

3.5. Enforcement Mechanisms and Penalties

Malaysia and Indonesia differ in their approaches to enforcing personal data protection. In Malaysia, enforcement is handled by the JPDP (Ministry of Communications), which can impose fines of up to RM500,000 or jail terms for violations. Enforcement is largely complaint- and audit-based. In contrast, as highlighted in Table 4.3, Indonesia's enforcement is planned to be managed by a Data Protection Authority (yet to be established), with penalties reaching up to Rp6 billion (approximately RM1.7 million or US$362,702). Indonesia employs both complaint-based and regulatory enforcement mechanisms.

For AI-powered agriculture startups aiming to expand regionally across ASEAN, these differences have strategic implications. Malaysia's more established enforcement structure offers a predictable regulatory environment, allowing startups to align their data governance and AI systems with clear compliance expectations. Meanwhile, Indonesia's evolving framework and higher penalties highlight the importance of proactive data protection practices, particularly for startups handling large volumes of farm, environmental, or farmer-related data. Startups must adopt strong data ethics, anonymisation, and security measures to minimise compliance risks and build trust amongst farmers and regulators. Learning to navigate these varying legal landscapes will not only strengthen operational resilience but also prepare startups for expansion into other ASEAN markets with similar emerging data protection regimes.

Table 4.3. Enforcement Mechanisms and Penalties Regarding Personal Data Protection in Malaysia and Indonesia

Aspect	Malaysia	Indonesia
Enforcement Body	JPDP (Ministry of Communications)	Data Protection Authority (to be formed)
Penalties	Fines up to RM500,000 or jail terms	Fines up to Rp6 billion (US$362,702)
Complaint Mechanism	Individual complaints and audits	Complaint-based and regulatory enforcement

Source: Author's data, 2025.

3.6. Opportunities for Harmonisation in ASEAN

With the rapid growth of the digital economy in Southeast Asia, there is increasing momentum towards regulatory convergence in personal data protection (PDP) laws across ASEAN Member States. Harmonisation efforts aim to reduce legal fragmentation, facilitate cross-border digital trade, and provide greater certainty for businesses operating regionally. Key initiatives include the ASEAN Framework on Digital Data Governance, which was published in 2018 and provides guiding principles for responsible data management; the ASEAN Model Contractual Clauses (MCCs) for Cross-Border Data Flows, designed to standardise contractual safeguards for international transfers of personal data; and the Digital Economy Framework Agreement (DEFA), currently under development, which seeks to establish common rules for digital trade, data protection, and interoperability across the region.

For agritech and livestock-focused AI startups, such as IPINFRA, these initiatives present significant opportunities. Harmonised data protection standards can simplify cross-border deployment of AI-driven platforms, enabling seamless transfer of farm and livestock data for predictive analytics, herd management, and cloud-based monitoring systems. Moreover, convergence of PDP laws could reduce the need for complex compliance strategies, accelerate regional expansion, and foster investor confidence in startups that rely heavily on sensitive agricultural and livestock data. Overall, ASEAN's push for regulatory alignment offers a pathway for digital agritech solutions to scale across multiple countries with lower legal and operational friction.

Building on this analysis, Chapter 5 will provide policy recommendations drawn from this study and our research on current regulations and policies affecting the adoption of AI technology in the agriculture sector, highlighting actionable strategies for startups and policymakers alike.

Chapter 5

Policy Recommendations

Building on the analysis of ASEAN's regulatory landscape, cross-border data considerations, and opportunities for harmonisation, this chapter outlines actionable policy recommendations to support the adoption and scaling of AI-driven technologies in the agriculture and livestock sectors. The recommendations are designed to address both regulatory and operational challenges faced by startups, with a focus on practical measures that enhance compliance, data governance, and stakeholder engagement. By translating the insights from previous chapters into targeted strategies, this chapter aims to guide policymakers, industry actors, and agritech innovators – such as IPINFRA – in implementing AI solutions that are effective, scalable, and aligned with national and regional frameworks.

1. Pilot Programme Implementation

A pilot programme is critical to testing and refining the AI-based cattle weight estimation system, assessing its practicality in real-world conditions, and ensuring it meets the needs of farmers. In addition to general industry engagement, direct collaboration with DVS Malaysia is critical to the successful implementation of the pilot programme. As the principal regulatory authority overseeing livestock health, welfare, and management practices, DVS provides essential guidance to ensure that the AI-based cattle weight estimation system adheres to established national standards. The department's involvement not only strengthens the technical and operational validation of the technology but also facilitates policy alignment, enhances farmer trust, and accelerates the integration of digital livestock solutions within Malaysia's agricultural modernisation initiatives.

1) Conduct Diverse Field Trials

- **Geographical Diversity**: Implement the pilot programme across a range of farm sizes, types, and geographical locations (e.g. small farms, large commercial operations, urban vs. rural settings) to assess how the AI system performs under different conditions.
- **Animal Diversity**: Test the system on different breeds, age groups, and sex of cattle, ensuring the model's adaptability to various livestock characteristics.

- **Environmental Variables**: Include different farming environments (e.g. open pasture, confined spaces, various weather conditions) to gauge the AI system's robustness under varying conditions.

2) Establish Benchmark Comparisons

- **Traditional vs. AI-Based Methods**: Conduct side-by-side comparisons of traditional weighing methods and AI-based weight estimations in terms of accuracy, time, cost, and ease of use.
- **Performance Metrics**: Use established performance metrics (e.g. MAE and RMSE) to quantify improvements in accuracy. Record feedback on usability, labour requirements, and animal stress.
- **Data Collection**: Gather data on AI model performance during these trials to refine and fine-tune the algorithm for improved accuracy and reliability.

3) Collaborate with Industry and Government Stakeholders

- **Public–Private Partnerships**: Work with agricultural organisations, technology companies, and government agencies to secure funding and technical expertise for the pilot programme. Collaboration with industry stakeholders ensures alignment with the latest technological advancements and regulatory requirements.
- **Government Support**: Engage with policymakers to secure their support for the programme, ensuring it aligns with national agriculture policies and economic development goals.
- **Farmers' Associations**: Partner with local farmer organisations to facilitate the involvement of smallholder farmers and provide them with incentives to participate in the trials.

2. Training and Awareness Programmes

To promote the adoption of AI-based livestock weight estimation technologies, policymakers and industry stakeholders should support initiatives that educate farmers and agricultural workers on the use, benefits, and operational requirements of such systems. Recommended actions include:

1) Develop Comprehensive Training Modules and Workshops

- **Hands-on Training:** Provide practical sessions where farmers can learn to operate the AI system, including capturing images, interpreting outputs, and troubleshooting common issues.

- **Blended Learning Formats:** Offer both online and in-person programmes to accommodate different learning preferences and regional accessibility.
- **Structured Curriculum:** Create step-by-step instructional guides, video tutorials, and skill-level–based modules to cater to beginners through advanced users.

2) Create Multilingual and Culturally Relevant Instructional Materials
   - **Localisation:** Produce materials in local languages to ensure accessibility in diverse regions.
   - **Visual and Infographic Guides:** Use illustrations and videos to support comprehension, particularly for farmers with limited literacy.
   - **Cultural Alignment:** Adapt training content to reflect local farming practices and scenarios for greater relevance and uptake.
3) Provide Robust Technical Support Services
   - **Helpdesk and Hotline:** Establish dedicated channels for farmers to report issues or request guidance.
   - **On-Site Support:** Deploy technical teams during initial rollouts to assist with setup and troubleshooting.
   - **Long-Term Support Structures:** Ensure sustained access to technical assistance, software updates, and operational guidance over time.

3. Integration with Existing Technologies

Policy support should encourage the seamless integration of AI-based livestock systems with existing farm technologies, enhancing operational efficiency and maximising the utility of collected data. Key recommendations include:

1) Link AI Apps with IoT and Farm Management Systems
   - **IoT Integration**: Link the AI weight estimation system with IoT devices – such as smart collars, GPS trackers, and Radio Frequency Identification (RFID) tags – to collect additional data (e.g. movement and feeding patterns) that can be used to improve weight predictions.
   - **Farm Management Systems**: Integrate the AI system with existing farm management platforms (e.g. crop and livestock tracking systems) to provide a holistic view of farm operations, enabling better decision-making.

- **Real-Time Data Collection**: Ensure that the system can collect real-time data from IoT devices and send it directly to the AI application for immediate processing and analysis.

2) Enable Cloud-Based Synchronisation
   - **Centralised Data Storage**: Use cloud-based platforms to store and manage large amounts of data from multiple farms, making it accessible remotely. This enables easy tracking of livestock data across different locations.
   - **Data Syncing**: Enable cloud synchronisation to automatically update data on all devices used by farmers, ensuring that they have access to the most up-to-date information at all times.
   - **Data Security**: Implement strong encryption and data protection measures to ensure the safety and confidentiality of farm data, including livestock health and performance information.

3) Develop API Frameworks for Interoperability
   - **Open API Standards**: Develop open Application Programming Interfaces (APIs) to facilitate the integration of the AI-based system with other agricultural technologies and software platforms.
   - **Third-Party Integrations**: Ensure the system can communicate with third-party tools used by farmers (e.g. accounting software, environmental monitoring systems, and veterinary records) to enhance the overall farm management ecosystem.
   - **Modular System**: Design the system to be modular, allowing farmers to customise the solution by integrating only the components they need, based on their specific operational requirements.

4. Regulatory and Policy Support

To enable the widespread adoption of AI-based livestock weight estimation systems, supportive regulatory frameworks are essential. These frameworks should ensure safety, ethical practices, legal compliance, and data protection, while also promoting equitable access for farmers. Recommended actions include:

1) Establish Standards and Certifications
   - **Quality Standards**: Develop national or international standards for AI-based livestock weight estimation systems to ensure the technology meets accuracy, safety, and reliability requirements.

- Certification Programmes: Create certification programmes for equipment manufacturers, software developers, and service providers to ensure that all products meet industry standards and are tested for effectiveness before being deployed.
- Regulatory Compliance: Ensure that the system complies with all local agricultural and technological regulations, including data collection, privacy, and animal welfare.

2) Advocate for Grants and Subsidies
    - Government Grants: Advocate for government grants and subsidies to help subsidise the cost of implementing AI-based systems for smallholder farmers, encouraging adoption in economically disadvantaged areas.
    - Public Funding: Encourage public funding for agricultural technology projects that focus on improving productivity and sustainability, particularly in rural or underdeveloped areas.
    - Partnerships with NGOs: Partner with non-governmental organisations (NGOs) to fund pilot programmes and provide financial incentives for farmers who adopt AI technologies.
3) Ensure Data Privacy Compliance
    - Data Protection Laws: Ensure that the AI system adheres to data protection regulations (e.g. GDPR in Europe and PDPA in Malaysia) to safeguard personal data collected from farmers and livestock.
    - Farmer Consent: Establish protocols for obtaining farmer consent before collecting, processing, or storing any data related to their farm or animals. Ensure transparency regarding how data will be used and stored.
    - Data Security Measures: Implement robust security measures (e.g. encryption and multi-factor authentication) to protect sensitive farm data and preent unauthorised access.

Chapter 6
Conclusion

The adoption of AI-based cattle weight estimation systems represents a significant advancement for Malaysia's livestock industry, addressing the limitations of traditional weighing methods, which are often time-consuming, costly, labour-intensive, and stressful for animals. By leveraging deep learning models, high-resolution imaging, and real-time processing, these systems allow farmers to estimate cattle weight quickly and accurately without specialised equipment or intensive labour. This technological shift enhances operational efficiency, reduces costs, improves animal welfare, and broadens access to advanced farming tools, particularly benefiting small- and medium-scale farmers across diverse regions.

Despite these advantages, the deployment of AI-based livestock solutions faces several challenges. High-quality and diverse datasets are required to train accurate AI models, and insufficient or biased data could compromise system performance. Many farmers may have limited experience with AI technologies or digital tools, necessitating comprehensive training programmes and ongoing support. Infrastructure gaps, such as limited internet connectivity in rural areas, can hinder real-time processing and cloud synchronisation, highlighting the need for offline-capable solutions. Additionally, stringent data privacy and security measures are essential to maintain the trust of farmers and comply with local and regional data protection laws.

Successful adoption and scaling of AI-based livestock weight estimation systems depend on strategic planning and multi-level collaboration. Well-designed pilot programmes, robust training initiatives, seamless integration with existing farm technologies, and strong regulatory frameworks are critical. Policy recommendations include implementing localised, offline-friendly consent mechanisms to comply with Malaysian and Indonesian PDP laws, fostering transparency in data usage and storage, anticipating cross-border constraints through hybrid cloud solutions, proactively engaging regulators via national innovation sandboxes, and promoting regional collaboration to harmonise AI regulations in agriculture across ASEAN. Support mechanisms such as government grants, public funding, certification programmes, and technical assistance can further incentivise adoption and ensure compliance with quality, safety, and animal welfare standards.

At the regional level, harmonisation efforts can facilitate lawful cross-border data flows and support startups seeking to expand AI solutions across ASEAN markets. Recommended actions include adopting ASEAN's Model Contractual Clauses (MCCs), establishing a Regional Agritech Regulatory Sandbox, convening annual bilateral dialogues between Malaysia's JPDP and Indonesia's Data Protection Authority, and integrating digital agriculture into the ASEAN Digital Economy Framework Agreement (DEFA). These measures create a more predictable and enabling environment for AI-driven agricultural innovations.

In conclusion, the integration of AI into livestock management heralds a new era for Malaysia's agricultural sector, marked by efficiency, sustainability, and resilience. By proactively addressing deployment challenges and investing in supportive infrastructure, regulatory frameworks, and regional cooperation, Malaysia can position itself as a leader in agricultural innovation within ASEAN. AI-based cattle weight estimation represents a critical first step toward a future of intelligent, efficient, and humane livestock farming.

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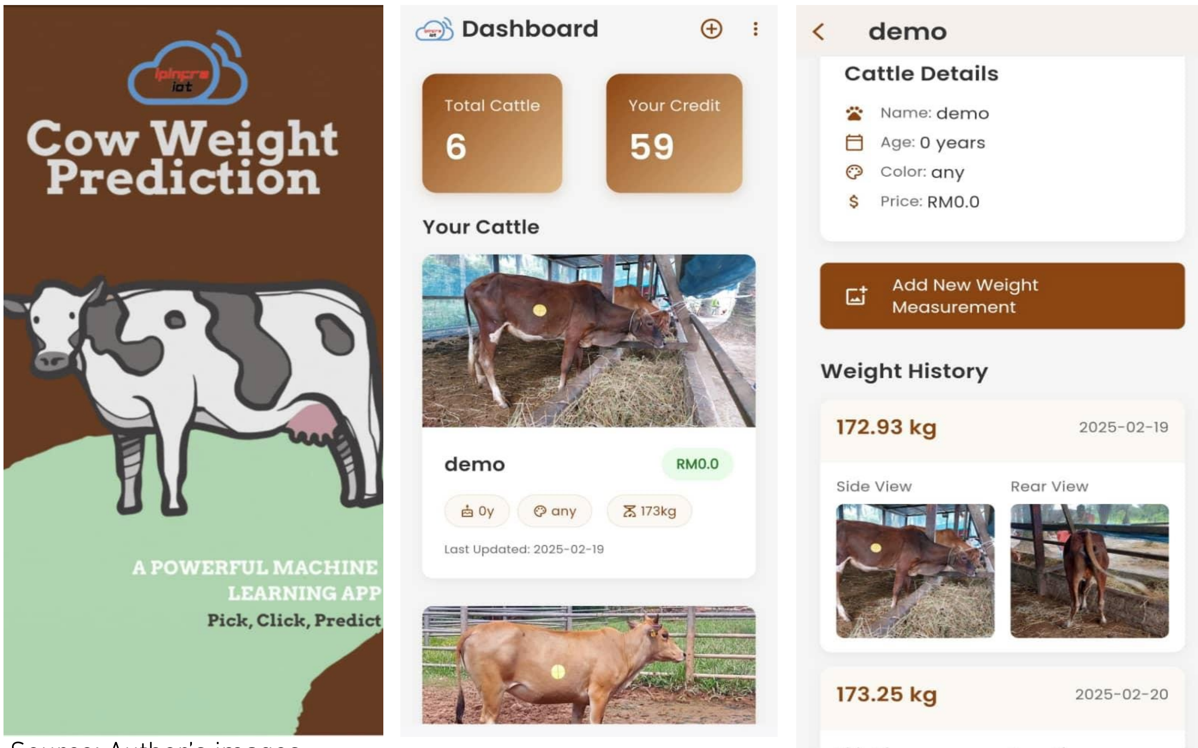
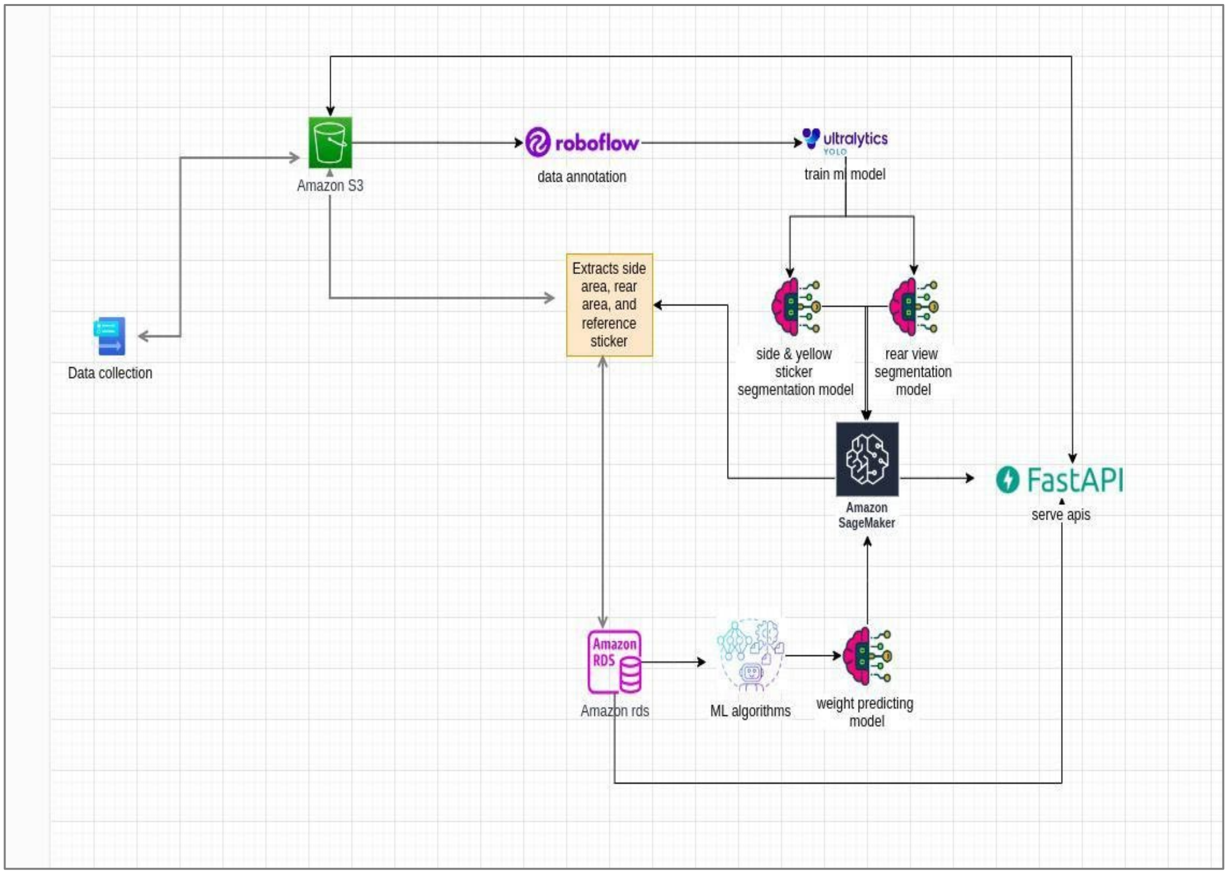
Appendices

Appendix A: Sample Images from the Cattle Weight Estimation Process Using IPINFRA's Application



Source: Author's images.

Appendix B: AI Model Development Framework



Source: Author's data.

Appendix C: Survey Questionnaire for Farmers and Stakeholders

Customer Feedback Survey: AI Cattle Weight

Company: IpInfra Networks Sdn Bhd

1. How did you hear about AI Cattle Weight?

- ☐ Social media (Facebook, Instagram, etc.)
- ☐ Website/Online search
- ☐ Referral from a friend or colleague
- ☐ Advertisement
- ☐ Other (Please specify) ___________

2. What is your primary reason for using AI Cattle Weight?

- ☐ To monitor cattle weight growth efficiently
- ☐ To reduce manual weighing costs
- ☐ To improve livestock health tracking
- ☐ Other (Please specify) ___________

3. How easy was it to set up AI Cattle Weight?

- ☐ Very easy
- ☐ Somewhat easy
- ☐ Neutral
- ☐ Somewhat difficult
- ☐ Very difficult

4. How accurate do you find the AI Cattle Weight system?

- ☐ Very accurate (matches manual weighing closely)
- ☐ Somewhat accurate (minor discrepancies)
- ☐ Neutral
- ☐ Somewhat inaccurate (needs improvement)
- ☐ Very inaccurate

5. How satisfied are you with the monthly pricing of RM30?

- ☐ Very satisfied (Affordable and worth the value)
- ☐ Satisfied
- ☐ Neutral
- ☐ Unsatisfied (Too expensive for the features)
- ☐ Very unsatisfied

6. What features would you like to see improved or added?

- ☐ More accurate AI predictions
- ☐ Better integration with farm management apps
- ☐ Additional livestock health tracking features
- ☐ More affordable pricing plans
- ☐ Other (Please specify) __________

7. Would you recommend AI Cattle Weight to other farmers?

- ☐ Yes, definitely
- ☐ Maybe
- ☐ No

8. Any additional comments or suggestions?

(Write your feedback here) ___________

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For submission to ERIA
Date: 25/4/2025