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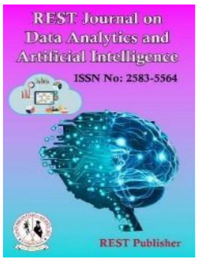

Computer Vision Driven Precision Dairy Farming for Efficient Cattle Management

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Abstract: *"Precision Dairy Farming (PDF)" or "The Per Animal Approach" can be enhanced through the implementation of three-dimensional computer vision, which offers improved cattle identification, disease monitoring, and growth assessment. The integration of 3D vision systems is particularly vital for advancing dairy farming practices in the next generation. These systems facilitate the automation of various animal husbandry tasks, including monitoring, herding, feeding, milking, and bedding of animals. The applications of 3D computer vision in PLF encompass diverse platforms, such as 3D camera installations for monitoring cow walking postures, and intelligent systems that interact safely with animals, capable of identifying dairy cattle and detecting health indicators like animal identification, recognition, body condition score, and lameness. To be effective, systems must be adaptable to unconstrained environments, varying herd characteristics, weather conditions, farmyard layouts, and animal-machine interaction scenarios. Considering these requirements, this paper proposes the application of emerging computer vision and artificial intelligence techniques in dairy farming. This review encourages future research in three-dimensional computer vision for cattle growth management and its potential extension to other livestock and wild animals*
Keywords: *Precision dairy farming, artificial intelligence, 3D vision, computer vision.*

1. INTRODUCTION

The dairy industry in India boasts a profound and extensive historical lineage, tracing its origins to antiquity. For millennia, milk and its derivatives have constituted an indispensable component of the Indian dietary tradition, while simultaneously nurturing a thriving culture of dairy husbandry and milk-oriented gastronomy. During the Vedic period (1500-500 BCE), milk, ghee, and curd were venerated as sacred substances, integral to religious rituals. Additionally, the Vedic era witnessed the domestication of bovine species, specifically cows and buffaloes, thereby laying the groundwork for the establishment of the dairy sector in India. Subsequently, during the colonial era, the British introduced contemporary dairy farming practices in India, motivated by the need to fulfill their demand for milk and meat. As a significant milestone, the inception of the first modern dairy in Aundh, Maharashtra in 1885 marked a pivotal moment in the modernization of the Indian dairy landscape. Notably, this was followed by the establishment of the Bombay Milk Scheme in 1948, aimed at supplying milk to the burgeoning city of Mumbai [1].Nevertheless; the landscape of dairy farming in India underwent a transformative shift with the advent of the White Revolution during the 1970s. Due to the growth boosting provided by the efforts of Dr. Verghese Kurien, today the Indian dairy industry stands as one of the most substantial and rapidly expanding sectors globally. Its remarkable growth has made it a significant contributor to the Indian economy, boasting a market size exceeding US$100 billion. A predominant characteristic of this sector is its prevalence among small and marginal farmers, who collectively possess approximately 80% of the country's bovine population. Remarkably, India holds the title of the world's largest milk producer, accounting for approximately 23% of the global milk production. As evidenced by data from the Department of Animal Husbandry and Dairying, the country's milk output for the fiscal year 2022-23 amounted to around 221.06 million metric tonnes [2]. Moreover, the sector has maintained a commendable compound annual growth rate (CAGR) of roughly 6% over the past decade. The latest concept in livestock farming is "Precision dairy farming (PDF)" which can counter the disadvantages of in-person monitored dairy farms. It pertains to a suite of real-time monitoring technologies engineered to proficiently oversee temporal variations within the most minimal viable production entity.

2. IMPORTANCE OF DAIRY FARMING

Indian dairy farming is usually associated with small and marginal farmers. Grazing farming was pronounced way of cattle rearing in India before late 1990's. The benefits of grazing encompass enhanced animal well-being[6], specifically with reduced occurrences of claw diseases [8], fertility issues [9]and mastitis[10]. This improvement in animal welfare has been confirmed through the implementation of the welfare quality protocol [7,16]. Furthermore, grazing farms demonstrate and reduced expenditures on feed[12,13,14] and lower labor costs[12,15] Now, the trend is shifting towards all year in-house dairy farms. Although, the all year in-house dairy farming has many cons but it is still favoured due to better cattle management, better nutrition and health monitoring with enhanced protection for cattle from harsh weather and predators. In-house cattle farms are further divided into large and small-scale farms. Considerable advantages are associated with large-scale commercial farms compared to their smaller counterparts. These benefits encompass a plethora of aspects, including enhanced access to proficient labor, comprehensive market insights, advanced technical expertise, robust financial resources and capital, effective risk mitigation strategies, facilitated market entry, and robust systems for product traceability and quality assurance [3]. There are many disadvantages associated with large-scale commercial dairy farms when compared with small-scale dairy farms like poor monitoring for individual cow for its nutrition, health, milk production etc. The adoption of new concepts like PDF can be beneficial in resolving such problems. PDF refers to a set of real-time monitoring technologies designed to effectively manage the temporal fluctuations within the smallest manageable production unit. This smallestmanageable production unit is denoted as 'the per animal approach' [4].The rapid advancements in Computer Vision (CV) and Artificial Intelligence (AI) have ushered in a myriad of prospects for enhancing the utility of these technologies in closely monitoring the individual requirements and behaviors of each animal. Furthermore, these advancements enable safe interaction between robotics and the animals [5].

2.1 Conventional techniques and their drawbacks: In the realm of contemporary intensive farming, the conventional approach to cattle growth management exhibits inherent flaws. This customary method relies on direct-contact tools or in-situ observations performed by humans; however, such human interventions are not without limitations. Firstly, the outcomes of this approach are susceptible to the subjectivity of the assessors. While experienced operators may strive to deliver high-quality results [19], their observations lack quantification and often fall short in detecting subtle or minor alterations [20,21]. Secondly, the traditional practices impose significant stress on both the animals and the individuals involved. The mere presence of humans can adversely affect the behavior of cattle, leading to stress-induced welfare issues as disturbances disrupt their natural disposition [17]. Simultaneously, the manual execution of operations puts human operators at risk of potential injuries [18]. Paradoxically, these subtle changes carry vital information that could prove immensely beneficial for individuals, particularly in the early detection of lameness.

2.2 Emerging tools: In the 18th century, machinery emerged with the primary purpose of handling simple tasks, such as wielding, rotation, and repetitive activities, thereby liberating human labor to focus on more intricate endeavors [22]. As the early 1900s dawned, the concept of machines assuming roles of heightened precision and supplanting human endeavors across diverse domains became a vision for the future. Recently, the advent of Artificial Intelligence, commonly referred to as AI, has astounded with its remarkable achievements, replacing humans in tasks like object recognition and computer vision [23]. Over the course of a few decades, automation has propelled the manufacturing sector and modern industries to unprecedented levels of productivity. Acting as a pioneering sector, the manufacturing industry paved the way for subsequent technological advancements that have profoundly influenced numerous other industries [24]. Over the past few decades, computer vision has emerged as a pervasive force, permeating diverse domains like 3D reconstructions, pattern recognition, machine learning, computer graphics, augmented reality, and virtual reality [25]. By the year 2010, computer vision had achieved remarkable feats in advanced tasks, including object recognition, autonomous vehicle navigation, face detection, fingerprint recognition, rapid image processing, and robotic navigation [26]. Fundamental techniques such as line detection, feature extraction, segmentation, feature matching and tracking, as well as 3D reality optimization and reconstruction, have sparked an array of astonishing innovations, such as visual simultaneous localization and mapping (SLAM) and object tracking [27]. The advent of Fourth Industrial Revolution (4IR) technologies, exemplified by computer vision and AI, has profoundly impacted various industries, including medicine, automotive, smart robotics, vision-based AI systems, and virtual agents. The observation of such technological progress has spurred a significant influx of investments into AI-based industries and services [29,30].

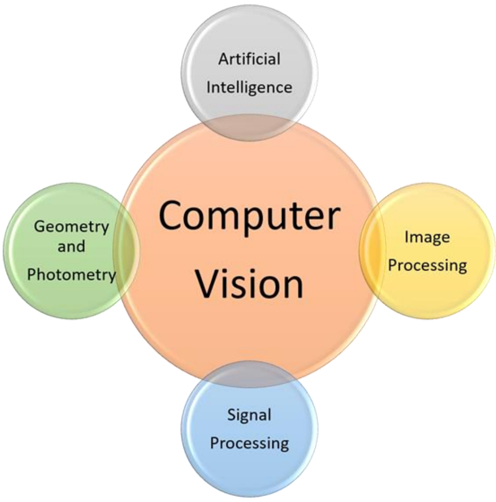


FIGURE1. Computer vision concept

The taxonomy of the computer vision field, as depicted in Figure 3, illustrates its interrelated branches, spanning science and technology, mathematics and geometry, physics and probability, and beyond. Notably, the integration of artificial intelligence techniques, especially machine learning and deep learning, necessitates extensive training data, which computer vision methodologies adeptly retrieve and process. Remarkably, the investments in computer vision-based startups alone have amounted to 3.5 billion USD, with nearly double the amount being channeled into AI machine learning-based startups, reaching 7 billion USD. [28]. In conclusion, the fusion of computer vision and AI technologies is reshaping industries across the spectrum, driving a surge of investment and fostering a new era of technological progress and innovative applications.

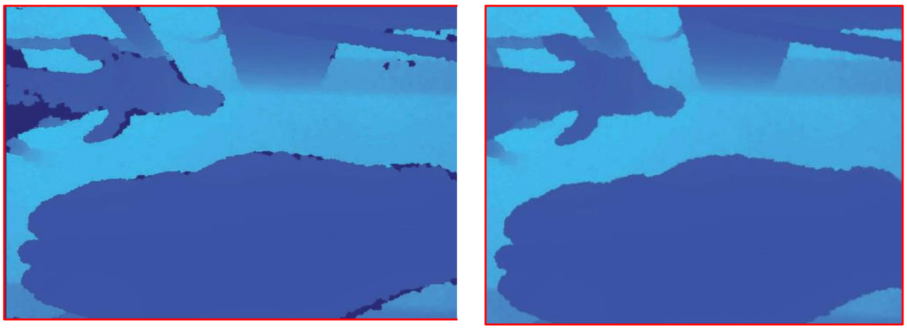
3. PRECISION DAIRY FARMING

In the realm of modern advancements, computer vision (CV) emerges as a pivotal force revolutionizing conventional approaches, particularly in the domain of PDF. This pioneering technology encompasses an array of methodologies, enabling seamless and non-intrusive monitoring and surveillance of individual livestock, with an acute focus on their well-being and overall health. Its practicality lies in real-time, direct, and remote observation, presenting farmers with invaluable insights and easily comprehensible data [31,32]. Central to this endeavor are sophisticated sensors generating refined data, coupled with intricate model analyses. By ingeniously amalgamating sensors and models, CV effectively streamlines cattle management, markedly reducing human intervention [33,34]. This transformative facet of CV, facilitated by cutting-edge two-dimensional (2D) and three-dimensional (3D) vision systems, renders traditional human observations replaceable, fostering a contactless and efficient approach in the pursuit of superior livestock husbandry [35]. The various applications of CV in modernizing the cattle farming are listed below: Animal Detection and Recognition, Lameness Detection, Body Condition Score Evaluation, Body weight and consideration, Body measurement assessment

3.1 Animal detection and recognition: According to the 2020 report from the Indian National Accounts Statistics (NAS), the livestock sector plays a significant role in contributing 4.19% to the total gross value added (GVA) and 28.63% to the total agriculture and allied sector GVA [36]. The identification of individual cow breeds holds promising potential for various farming opportunities, such as disease detection, prevention and treatment, fertility and feeding optimization, and welfare monitoring. However, accurately identifying and detecting cow breeds pose challenges due to the vast number of cows belonging to numerous breeds, many of which have almost identical visible appearances. This renders the task of precise identification and detection tedious. Therefore, automating the process of cow breed detection would prove highly beneficial to the dairy industry [37]. Although traditional object detection algorithms like RCNN, fast RCNN, and faster RCNN provide accurate detection, they suffer from slower processing speeds [38]. To address this issue and improve detection speed, a single-shot detector (SSD) has been introduced, capable of detecting multiple objects at an impressive rate of 22-59 frames per second (FPS) [39]. One example of these advanced SSD tools is YOLOv4. YOLOv4, unlike conventional CNN architectures, offers fast and accurate detection, making it particularly suitable for real-time applications. Overall, the experimental results demonstrate that enhancing the model's accuracy involves training YOLOv4 on high-resolution images, utilizing a greater IoU threshold, thereby achieving improved performance [37].

3.2 Lameness detection: Dairy cow lameness not only exerts detrimental effects on bovine welfare and diminishes dairy production but also compromises reproductive capabilities and augments mortality rates [40-42]. The average incidence of lameness in dairy cows stands at 23.5% as per the Research Report published by Goldman Sachs [43]. This rate exhibits considerable variation among countries, attributed to diverse pasture production conditions and grazing practices, yet cow lameness remains a pervasive concern on farms worldwide [44]. The significant prevalence of lameness bears substantial ramifications for the dairy economy [45,46], with treatment costs associated with this condition ranking second among common dairy ailments [47]. Consequently, numerous studies have diligently endeavored to investigate the root causes of lameness and potential mitigation strategies. Remarkably, locomotion scoring, a method employed by farmers to identify lame cows, merely captures an average of less than 35% of the total lame population on a farm [48].Automated lameness detection represents a promising avenue to address crucial information gaps concerning the condition of individual cows and the herd as a whole, with a particular focus on identifying cases of mild and moderately lame cows [49]. It is worth noting that the range of available camera technologies, including 2D cameras, 3D cameras, and thermal infrared cameras, varies widely in price [50]. Pioneering the utilization of a 2D computer vision technique, this study embarked on cow lameness detection research by curating a comprehensive dataset comprising walking cow videos [51]. The compelling results showcased the efficacy and reliability of integrating the 2D computer vision technique alongside a digital rating system for accurate lameness detection. In comparison to manual detection methods, while the automated system incurs initial equipment costs, the potential benefits of embracing automated lameness detection far outweigh these expenses [52]. It is essential to acknowledge that data gathered through cost-effective cameras may introduce challenges in post-processing, such as ghost images, which can subsequently impact the integrity of test results [50].

3.3 Body condition score evaluation: Body Condition Score (BCS) serves as an indirect gauge of the body's reserves, capturing the cumulative fluctuations in energy balance [5]. Its association with reproductive and health performance renders it a crucial consideration in dairy production, albeit challenging to monitor effectively. Traditional manual visual BCS evaluation is fraught with subjectivity, demands substantial time, and necessitates experienced personnel [53-55]. However, advancements in techniques like Computer Vision (CV) and 3D image analysis have emerged as a boon, outperforming conventional BCS assessments conducted by trained individuals. The application of 3D vision-based animal monitoring systems has demonstrated their exceptional capacity to identify individual cows, thus offering real-time insights into their health status [56]. This empowers the incorporation of valuable data into feeding systems, enabling more precise cow nutrition management and timely alerts to the farmer in case of potential health issues. These 3D CV systems commonly analyze cattle's 3D back images captured from a top-down perspective [55]. Such images yield specific dorsal traits, which are utilized as inputs for the models. The extraction of direct acquired dorsal traits, including dorsal length, and directly calculated traits like dorsal area and convex hull volume, forms the basis for BCS estimation [53,54]. In a notable study, multiple 3D cameras were strategically placed at various angles to emulate human assessors scrutinizing different body regions of cows from distinct views. This innovative approach significantly improved the accuracy of BCS classification [35]. The quantification of bovine height, achieved through the meticulous analysis of 2650 images captured by the Kinect v1 camera (Figure 2), was undertaken by assimilating crucial factors such as the curvature of the cow's back, age, and weight. The resultant findings astoundingly revealed an impressive 74% accuracy level, accompanied by a remarkably low error margin of merely 0.25% [57]. The body weight (BW) consideration and body measurement assessment (BMA) are easily done with the help of computer vision and analyzing the 3D images various researches has been completed in this regard. In this captivating and scholarly context, the estimation models employed distinctive features derived from 3D data acquisition and pre-processing, serving as the explanatory variables [5]. These encompassed intricate 3D body measurements, age-related information, and various parameters calculated from the 3D body measurements [54]. To estimate body weight, the approach embraced Mirtich's pioneering theory (1996) [58], ingeniously combining the essence of both the divergence theorem and Green's theorem. Through this ingenious integration, Green's theorem artfully computed the surface area of the 3D mesh, while the divergence theorem deftly ascertained the volume based on the aforementioned area [59]. Furthermore, a compelling study conducted has established that the precision of measurements is significantly influenced by variables such as fur type, fur color, and the velocity of movement [60].



(A) (B)

FIGURE 2. Image before (A) and after (B) restoration [57]

4. POTENTIAL CHALLENGES ASSOCIATED WITH USAGE OF COMPUTER VISION

Using CV and 3D image analysis for PDF can bring several challenges. Factors such as lighting conditions, animal movement, and environmental obstacles can interfere with the quality of the images captured. This can lead to inconsistencies and inaccuracies in the analysis, affecting the effectiveness of the system. The various potential challenges associated with application of CV in cattle farms are listed in Table 1.

TABLE 1. Challenges of using computer vision in dairy farms

Sr. No.	Challenges	Explanation
1	Data quality	Acquiring reliable and high-quality image data can be challenging due to factors like varying environmental conditions, lighting, and camera limitations.
2	Accuracy and Precision	Ensuring precise and accurate measurements from computer vision and 3D analysis is crucial for making informed decisions in dairy farming.
3	Complexity of Image Processing	The analysis and processing of large volumes of images and 3D data often require substantial computational resources and specialized algorithms.
4	Learning and Adaptation	Continuous learning and adaptation may be necessary for computer vision systems to accommodate changes in farm conditions and animal behavior.
5	Ethical and Privacy Concerns	The use of image analysis may raise ethical considerations and privacy concerns regarding animal treatment, necessitating adherence to guidelines.
6	Cost and Infrastructure	Implementing computer vision and 3D analysis systems can be costly, requiring investments in technology, hardware, and skilled personnel.

5. CONCLUSIONS

PDF is a rapidly developing field that utilizes computer vision to enhance various aspects of dairy farming operations. Computer vision, a branch of artificial intelligence that enables machines to interpret and understand visual information, has the potential to revolutionize the way dairy farmers manage and monitor their herds. This technology provides several associated benefits, such as improved productivity, increased animal welfare, and enhanced decision-making capabilities. One of the key benefits of computer vision in PDF is its ability to accurately monitor the health and behavior of individual cows. By analyzing visual data, such as body posture, feeding behavior, and even facial expressions, computer vision systems can detect early signs of illness or distress, allowing farmers to intervene promptly to ensure the well-being of their cows. This proactive approach to health management can lead to reduced veterinary costs and improved overall herd health. In addition to health monitoring, computer vision in PDF can also aid in optimizing feeding and nutrition management. By analyzing the behavior and consumption patterns of individual cows, these systems can detect deviations from normal feeding patterns and adjust feed allocation accordingly. This targeted feeding approach not only ensures that each cow receives the appropriate amount and type of feed but also minimizes waste and costs associated with overfeeding. Furthermore, computer vision can assist in reproductive management by accurately identifying cows in estrus or heat. By monitoring behavioral cues and even physical changes, such as swelling or discharge, these systems can alert farmers to the optimal timing for artificial insemination. This precise timing can significantly increase the success rate of pregnancies and ultimately improve the breeding efficiency of the herd. Another advantage of computer vision in PDF is its role in monitoring and managing cow comfort. By analyzing the postures and movements of cows, these systems can identify discomfort-inducing factors, such as inadequate bedding or overcrowding. Farmers can then make informed decisions to improve housing conditions, layout, or ventilation, leading to increased animal welfare and productivity. In conclusion, computer vision has the potential to revolutionize PDF by providing accurate and real-time insights into cow health, behavior, feeding, reproduction, and comfort. There are some drawbacks associated with applications of CV in dairy farms such as complexity in installation, high cost of CV system, requirement of trained employees, and potential damage to setup by cattle. But, with proper planning, designing and installation of CV system for PDF can be a game changer for Indian dairy farming. By leveraging this technology, dairy farmers can proactively manage their herds, leading to improved productivity, enhanced animal welfare, and more informed decision-making. The ongoing advancements in computer vision algorithms and hardware will undoubtedly fuel further innovation and adoption of this technology in the field of PDF**.**

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