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Artificial Intelligence-Based Automated Barn Climate Management

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Abstract: High air temperatures caused by climate change affect various aspects of daily life, including the livestock sector. In dairy farming, heat stress in cows emerges as a major issue, reducing both animal health and milk productivity. To mitigate these effects, farmers commonly use barn cooling and climate control systems. However, these traditional systems lack intelligent decision-making mechanisms. This study focuses on the integration of an AI-powered image and data processing model into existing cooling systems to improve efficiency and establish a sustainable infrastructure. Through the use of artificial intelligence, the cooling systems are expected to operate more sensitively and efficiently, adapting to changing environmental conditions while minimizing resource usage. The impact of cooling systems on livestock productivity is analyzed, and improvements are proposed for more effective use. The integration of image processing and AI-based models is evaluated in terms of operational efficiency. Reducing resource usage through smart systems is emphasized as a key advantage. The system aims to ensure animal welfare and health with minimal resource consumption, by automating climate control systems and enabling intelligent decision-making processes. As a result, operational costs are expected to decrease and system stability to increase. Additionally, the study discusses the potential benefits of a real-time system for operational management. Real-time monitoring of animal behavior and automated system responses are explored for their potential to improve farm management. Experimental results showed that the proposed system achieved an average response time of 1.8 seconds, a 28% reduction in water consumption compared to traditional systems, and a cow detection accuracy of 91.2% mAP, confirming its effectiveness in real-time barn environments.

Key words: Artificial intelligence, image processing, smart systems, livestock farming, milk productivity.

Yapay Zekâ Tabanlı Otomatik Ahır İklim Yönetimi

Öz: İklim değişikliğinin sebep olduğu yüksek hava sıcaklığı günlük yaşam rutinleri içerisinde birçok alanı etkilemektedir. Hayvancılık alanı için örnek vermek gerekirse süt sığırlarında ısı stresi durumunu ortaya çıkarmaktadır. Isı stresi hayvanların sağlığını ve süt verimliliğini düşürdüğü için bu işletmeler ahırlarda çeşitli serinletme ve iklimlendirme sistemleri kullanmaktadır. Ancak bu sistemler geleneksel olup akıllı kararlar alan bir mekanizmaya sahip değildir. Bu çalışmada işletmelerin verimliliklerini arttırmak ve sürdürülebilir bir yapı oluşturabilmek adına serinletme sistemlerine yapay zekâ destekli görüntü ve veri işleme modeli entegrasyonu üzerinde durulmaktadır. Yapay zekâ modeli sayesinde kurulu olan serinletme sistemleri daha duyarlı ve etkili hale geleceğinden, değişen ortam koşullarında daha doğru çalışan ve kaynak kullanımını azaltan bir serinletme sistemi sağlanması hedeflenmektedir. Serinletme sistemlerinin hayvanların verimlilikleri üzerindeki etkileri araştırılmakta ve bu sistemlerin daha etkili verimli kullanılabilmesi adına geliştirmeler yapılmaktadır. Sistemin yapay zekâ ve görüntü işleme modeli ile çalışması verimlilik açısından değerlendirilmektedir. Akıllı sistemlerin entegrasyonu sonucunda kaynak kullanımının azaltılması üzerinde durulmaktadır. Hayvan refahı ve sağlığının daha etkili ve az kaynak kullanımıyla sağlanması, serinletme sistemlerinin otomatize ve akıllı karar mekanizmalarıyla çalışması ve sonuç olarak işletme maliyetlerinin minimize edilerek kararlılıklarının arttırılması hedeflenmektedir. Bunun yanında gerçek zamanlı çalışan bir sistemin işletme üzerinde ne gibi avantajlara sahip olabileceği tartışılmaktadır. Hayvan sağlığı üzerinde gerçek zamanlı takibin hayvan davranışlarını inceleyerek anlık sistem tepkileri üretilmesinin faydaları araştırılmaktadır. Gerçekleştirilen testler sonucunda, sistemin ortalama 1.8 saniyelik tepki süresi ile çalıştığı, geleneksel sistemlere kıyasla %28 oranında su tasarrufu sağladığı ve inek tespitinde %91,2 mAP doğruluğu elde ettiği belirlenmiştir.

Anahtar Kelimeler: Yapay zekâ, görüntü işleme, akıllı sistemler, hayvancılık, süt verimliliği.

1. Introduction

One of the primary challenges faced by dairy farms is high air temperatures. Elevated temperatures cause heat stress in dairy cows, which disrupts the balance between body heat production and dissipation. The body heat generated, also known as basal heat, is influenced by ambient temperatures. The thermal neutral zone, the

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temperature range in which cows can maintain their normal body temperature, is determined to be 4.5–26.5°C. Within this range, the basal heat production is approximately 825 kilocalories per hour. When the temperature exceeds 26.5°C, the body's heat production decreases by about one-third. This reduction leads to decreased activity, reduced feed intake, and consequently, lower milk production in cows. If adequate shading is not provided, the radiant energy from the sun exacerbates the stress experienced by the animals [1]. To reduce stress and restore normal bodily functions in cows, various interventions such as providing shade, enhancing passive ventilation, and adding fans and sprinklers can be implemented. Effective cooling lowers the animals' body temperature, maintains basal heat balance, and improves milk production efficiency [2]. Methods employed to help cows maintain their basal body temperature and achieve cooling can mitigate the inefficiencies caused by heat stress [3]. Keeping barns cool prevents the onset of heat stress in animals, ensuring productivity remains at optimal levels. Conversely, studies have shown that even brief exposure to moderate heat can increase respiratory rates and elevate animal body temperatures. This rise in body temperature reduces heat production below normal levels, leading to reduced activity and feed intake. A decrease in feed intake significantly lowers metabolic activities, resulting in a loss of milk production. Even with changes to feeding practices, feeding schedules, and supplementary additives, the losses in milk production caused by heat stress cannot be fully mitigated. This is because stressed animals exhibit a lack of appetite, preventing them from consuming adequate nutrients necessary for optimal milk production [4].

Modern dairy farms employ various methods to enhance animal welfare and ensure effective cooling. Sprinkler systems, which spray water to cool animals, are widely used to maintain the health and comfort of livestock. Additionally, providing shaded areas is essential to protect animals from the effects of solar radiation, helping to keep body temperatures low and maintaining basal heat production within normal ranges. Combining shade with sprinklers and fan-based ventilation systems in barns has been shown to significantly reduce respiratory rates and body temperatures in animals, enabling metabolic functions to proceed without disruption [5]. Another cooling method is the use of misting systems, which release a fine cold vapor to cool the surrounding air. However, misting systems are generally less effective than sprinklers in achieving desired cooling levels. This is because cold air, particularly in hot and confined barn environments, does not provide the same cooling effect as water. Fans are another common solution, especially in smaller-scale or less advanced farms, where they are used to circulate and direct air to cool animals. Yet, studies have consistently shown that cows cooled with sprinkler systems produce more milk compared to those cooled solely with misting or fan systems [6]. Despite their effectiveness, sprinkler systems consume ten times more water than misting systems, raising concerns about water usage efficiency. The operational costs associated with sprinkler systems can escalate in farms that fail to use these systems effectively and strategically. Therefore, it is crucial for farms utilizing sprinkler systems to adopt technologies that enhance efficiency and reduce operational costs in cooling systems. Another critical factor influencing the effectiveness of animal cooling is the duration and frequency of water spraying. If water is sprayed for excessively long periods, it leads to excessive water consumption and increased operational costs, which is undesirable. Conversely, insufficient spray durations fail to provide adequate cooling and offer no substantial benefits for milk production. Research highlights the importance of optimizing water spraying performance; overly frequent sprays result in unnecessary water wastage, while infrequent sprays diminish the cooling effect [7]. While these cooling methods are vital for productivity, they lack intelligent decision-making mechanisms. As a result, they are insufficient in responding to variable environmental conditions, highlighting the need for integrating smart systems into cooling processes.

With advancements in technology and its application to industrial sectors, operational efficiency in businesses has seen positive transformations. Improvements and innovations driven by artificial intelligence (AI) and image-processing algorithms have made production processes more effective in terms of both efficiency and sustainability. Adapting to the advancements and innovations introduced by Industry 4.0 has become a necessary step for businesses to remain competitive within their respective sectors. These innovations not only reduce resource consumption but also enable increased production and profitability. As a result, digital transformation and keeping pace with technological developments have become critical topics for the livestock industry and its stakeholders. Incorporating these advancements into the livestock sector is essential for ensuring sustainable growth and operational competitiveness [8].

Monitoring and evaluating the health, posture, and behavioral patterns of livestock in dairy farms is of paramount importance. Therefore, tracking animals to assess their condition and behaviors becomes a necessity. Real-time monitoring of animals allows for accurate assessment of their health status, water and feed consumption, heat and stress conditions, and provides opportunities for timely intervention by farm operators. Additionally, barns' integrated cooling systems can be monitored and controlled effectively. Several methods enable the implementation of these systems. For instance, camera systems installed in barns can analyze the positions and movements of animals, allowing the establishment of smart systems that enhance operational efficiency. In the face of increasing demand in the dairy industry, ensuring maximum growth with minimal operational costs has become essential. This goal can only be achieved through the integration of advanced technologies that enhance efficiency, sustainability, and animal welfare [9]. Minimizing resource use while maximizing efficiency has made the adoption of artificial intelligence (AI) and image-processing technologies a highly advantageous approach. Livestock can be monitored in real-time by employing AI and image processing, and automated decision-making and evaluation mechanisms can be integrated into barn systems. A subtraction-based approach has been effectively used to track animal behaviors in dairy farms, particularly for monitoring posture and movement using image processing techniques aligned with the aim of this study [10] . Specifically, numeric images of areas occupied by animals are compared to empty-background images (such as pens, pastures, or bedding areas) of the same spaces. This method enables real-time monitoring and learning of animal positions and behaviors, facilitating enhanced decision-making for farm operations [11].

Numerous studies in the literature focus on barn climate control systems and their effectiveness in reducing heat stress in livestock. Firfiris et al. [12] presented research on the application of passive cooling systems, successfully implemented in urban buildings, to livestock housing. Their review study concentrated on construction principles for the most common passive cooling systems in farm buildings. They emphasized the importance of energy-efficient cooling systems for modern and sustainable farm structures. Zhang et al. [13] provided a comprehensive overview of individual precision cooling methods for dairy cows, including spray cooling, forced air convection, and waterbed cooling. They also evaluated the adaptability of technologies such as infrared thermography, computer vision, and wearable sensing devices for detecting heat stress. The study highlighted the limited use of automated control systems in dairy farms and stressed the importance of control logic in precision cooling. By proposing the integration of real-time monitoring and control strategies, they contributed to enhancing the efficiency of existing cooling systems. Liberati [14] developed an active drying sensor to optimize sprinkler and ventilation systems for cooling dairy cows. The sensor simulated the thermal responses of cows to predict fur drying time, achieving a 57% reduction in water consumption. This study made a significant contribution to using sensors in assessing heat stress and improving resource efficiency. Cao et al. [15] investigated the effects of discharge angle on cooling efficiency in ventilation systems based on perforated air ducts (PAD). Using computational fluid dynamics simulations, they examined the impact of various air flow rates, duct diameters, and deflector types. The results indicated that rectangular duct deflectors provided the highest convection heat transfer rate, making discharge angle optimization a promising method for enhancing the performance of PAD systems. Garcia et al. [16] conducted a study on a low-profile cross- ventilated (LPCV) barn equipped with evaporative cooling pads to reduce heat stress in dairy cows. Analyzing 5,712 data records, they observed that LPCV systems were more effective under low-humidity conditions, achieving an indoor-outdoor temperature difference of up to −12°C. Their experimental findings revealed that LPCV systems increased the time cows spent in thermoneutral conditions and significantly reduced heat exposure when temperatures exceeded 25°C. They concluded that LPCV systems are a viable alternative for managing dairy cows in hot and humid climates. These studies collectively underscore the critical role of innovative climate control systems in enhancing animal welfare and productivity in dairy farming, offering valuable insights for integrating advanced technologies into barn operations.

In this study, an artificial intelligence (AI)-based model has been developed to prevent heat stress in livestock on dairy farms and enhance the efficiency of cooling systems. The proposed model leverages image processing techniques to optimize cooling processes, aiming to minimize human-induced errors while improving the efficiency of water, energy, and labor usage. The system enables individual recognition and monitoring of animals, providing farms with a cost-effective and sustainable solution. This study aims to develop an artificial intelligence (AI)-based model for preventing heat stress in dairy livestock by optimizing cooling systems through image processing techniques. The proposed approach focuses on enhancing the efficiency of water, energy, and labor use while supporting sustainable and cost-effective livestock management practices.

The remainder of the study is structured as follows: Section 2 focuses on the Materials and Methods, covering the motivational drivers behind the study, its general limitations, and the methodologies employed for analyses. Section 3 presents the experimental studies conducted, while Section 4 details the findings derived from these experiments. The Discussion is provided in Section 5, followed by the Conclusion in Section 6, which summarizes the key outcomes of the study and concludes the paper.

2. Materials & Methods

The Materials and Methods section explains the motivational drivers and limitations of the study, detailing the methodologies employed. This section covers the processes followed in developing the AI-based model and the data analysis approaches used.

2.1. Motivations

This study aims to optimize barn cooling systems used to prevent heat stress in livestock on dairy farms. By integrating an artificial intelligence (AI)-supported image processing model, the proposed approach seeks to reduce human-induced errors while minimizing resource usage (water, electricity, and labor), thereby enhancing overall efficiency. Additionally, the study focuses on maintaining and improving the consistency of milk production in livestock and evaluating the impact of technology adoption on farm productivity. These objectives represent key aspects addressed within the scope of the research.

The integration of artificial intelligence (AI) technology into traditional cooling methods plays a pivotal role in mitigating the adverse effects of heat [17]. In this context, the aim is to guide cooling systems through intelligent decision-making mechanisms and achieve full automation. The proposed model was developed to automatically manage barn cooling systems by analyzing real-time image data and environmental sensor inputs. It consists of several key stages, including background subtraction, animal detection, and the integration of temperature and humidity data. These components work in coordination to determine when and where cooling is required, thereby minimizing unnecessary water and energy use. A visual summary of the system's structure and operation is provided in Figure 1.

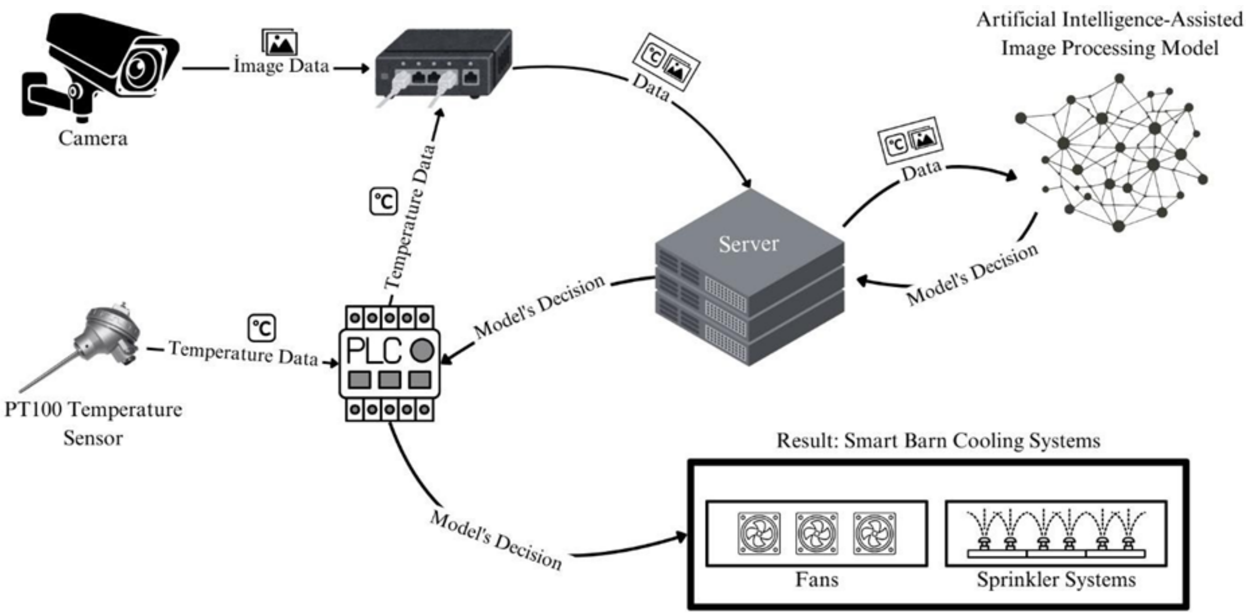

Figure 1. Visual summary of the study.

However, there are certain limitations in the implementation of the system. The creation of a real-time, remotely manageable system may encounter issues such as internet and electricity outages. Additionally, hardware components are exposed to challenging environmental factors such as humidity, dust, and high temperatures in barn conditions. This can lead to malfunctions in electronic connections and impose constraints on the selection of appropriate hardware. In this context, AI-supported models to be used in dairy farms must be carefully designed, considering these limitations.

2.2. General Limitations in Smart Barn Climate Control Systems

I. Limited Case Studies in Livestock Enterprises:

While the agricultural sector strives to adapt to the innovations brought by Industry 4.0, this transition is occurring at a slower pace than other industries. This creates opportunities for unique research within the sector but also presents significant challenges. Adapting systems implemented in different industrial domains to the agricultural sector and developing new methodologies has become a necessity [18]. However, businesses, universities, and research centers are faced with the need to increase research and development efforts to overcome the challenges encountered during this adaptation process.

II. Data Insufficiency and Reliability:

Traditional barn cooling systems generally lack the capability to generate and store sufficient data. This leads to issues such as the inability to access historical data and the absence of preliminary analysis processes. Interpreting a system with the support of artificial intelligence models, especially for systems that have not previously generated data, is a challenging task. In cases of missing data, performing statistical analysis and interpreting the gaps requires additional effort. In this context, during the process of making the system intelligent, detailed analyses and tests should be conducted to identify potential issues preemptively, and solutions should be developed accordingly [19].

III. Lack of Technological Infrastructure and the Risk of Hyper-Connectivity:

The instability of internet connection can pose a significant barrier to real-time data generation and analysis, potentially leading to system malfunctions and a decline in the performance of technological equipment. Such a situation can compromise system efficiency and degrade the performance of technological assets. Furthermore, the risk of hyperconnectivity is rooted in the complex interdependencies among the business's subunits. A problem in one subunit has the potential to cascade to other areas, causing systemic disruptions [20]. Hence, measures should be taken to minimize these risks during the design and integration of systems.

IV. System Optimization Issues:

The primary goal in the establishment of technological systems is to enhance the efficiency of businesses. However, achieving this objective requires not only the effective utilization of resources but also the optimization of the systems themselves. Unoptimized systems can lead to a loss of efficiency from the business perspective. Moreover, creating an optimized system with limited resources is a challenging process. Proper adjustment of parameters and optimization of existing systems are fundamental strategies to increase efficiency and ensure long-term sustainability [21].

V. Difficulties in the Harmonious and Efficient Operation of Barn Air Conditioning Systems:

The combined use of fan and sprinkler systems for cooling livestock can face various challenges during implementation. For instance, running sprinkler systems for an excessively long period can increase water costs without providing effective cooling for the animals. Similarly, if fans are turned off while the sprinklers are running, it may lead to heat stress. To address these issues, innovative solutions should be developed that optimize resource usage and ensure the systems work in harmony, improving the overall efficiency and effectiveness of the cooling process.

VI. Limitations in Selection of System Subunits:

The challenging environmental conditions in barns, including dusty, wet, and humid environments, necessitate the use of equipment that is resistant to such conditions. In addition, selecting appropriately sized, high-performance equipment suitable for confined spaces like barns is crucial. For equipment that cannot be placed inside the barn, suitable design plans must be developed to ensure effective integration. Such evaluations help prevent increased costs and damage to equipment, thereby enhancing the sustainability of the system.

2.3. Data and Obtaining Methods

The system continuously collects data from PT100 temperature sensors and HIKVISION cameras within the barn environment. These collected data are transmitted to the artificial intelligence-based image processing model through various system components using communication protocols such as Real-Time Streaming Protocol (RTSP) and Modbus Transmission Control Protocol (Modbus TCP) via Ethernet connections. RTSP is used for transmitting image data, while Modbus TCP is employed for transmitting temperature data to the PLC and network [22]. This data transmission enables real-time operation of the model, allowing the barn climate control systems to be guided based on live data. Furthermore, the data collection process requires seamless integration of components such as the PLC (Programmable Logic Controller), server, andartificial intelligence model. The entire data flow and collection process are visualized in Figure 2.

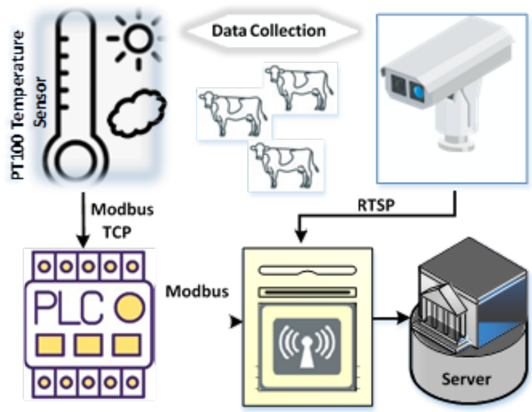

Figure 2. Demonstration of the data collection process.

Figure 2 illustrates the flow of temperature and image data within the system in detail. Additionally, another critical type of data obtained from the enterprise pertains to milk production. This data is collected separately from the barn environment for analytical purposes and is safeguarded in accordance with the enterprise's privacy policies. Consequently, specific details regarding the methodology for calculating the average milk production and enterprise data cannot be disclosed. The data can be represented as follows:

Temperature: The PT100 temperature sensor functions by altering its resistance value based on temperature, serving as a reliable component for temperature measurement in the barn environment. This sensor is known for its precision and robustness and ensures dependable temperature monitoring [23]. It transmits the measured temperature data to the system via the PLC. The PLC subsequently forwards this data to the server, where it is used as a parameter for the artificial intelligence model. The AI model processes the temperature data through its intelligent decision-making mechanism and activates the cooling system at the optimal time. This ensures the system operates efficiently, adapting dynamically to temperature variations, thereby enhancing the overall effectiveness of barn climate control.

Image Data: Visual data from the barn environment is captured using HIKVISION DS-2CD1643G0-IZS/UK cameras, which are specifically designed for challenging environmental conditions. These cameras feature high-resolution imaging, adaptability to low-light settings, and resistance to dust and moisture, making them ideal for barn use. Their wide field of view and ability to track animal movements in detail ensure superior performance in image-processing applications [24]. Raw images captured by the cameras have a resolution of 2688x1520 pixels before any preprocessing. Prior to being fed into the algorithm, the image dimensions are adjusted to meet model requirements. The captured images are transmitted to the server via the RTSP (Real-Time Streaming Protocol) and subsequently sent to the AI model for analysis. The AI model processes these images to determine the positions of the cattle using image processing techniques. Positional data is then compared with predefined area coordinates, such as feeding zones (paddocks) or sprinkler system ranges, to ascertain whether the animals are within these regions. Based on this information, the model makes decisions to optimize barn climate control systems and enhance animal welfare, ensuring efficient and responsive system operations.

Restricted Area Coordinates: To enable the AI model to effectively process images and interpret the positional data of the cattle, a set of restricted areas is defined for each camera. These areas are uniquely tailored to the barn's layout and are designed to overlap with functional zones, such as the feeding area (paddock) and the sprinkler system range. This ensures precise monitoring and control of the barn's climate and feeding systems. The restricted areas are delineated on the images by drawing bounding boxes corresponding to the designated zones. These boundaries are defined based on the barn's architectural design and operational requirements. Once the zones are mapped, the number of cattle within each boundary is calculated in real-time. The AI model uses this data to make decisions according to predefined thresholds and conditions, ensuring that system responses align with the actual distribution of cattle in the barn.

Milk Production Data: The data taken from the farm where the study was carried out, is provided by the business. The data was used to make various analyses and to observe the developments regarding the contributions of the study. The farm collects and calculates milk production data with its own unique methods.

Transmission and Storage of Data on the Server: A server is essential for real-time data monitoring and image processing, serving as a hub to store incoming data, provide an analytical environment, and relay decisions to system components [25]. However, the server must be installed in a protected area due to challenging barn environments—characterized by dust, heat, moisture, and water exposure. The durability of servers is determined by their Ingress Protection (IP) ratings, such as IP54 and IP65, which indicate resistance to dust and water ingress [26]. Additionally, the optimal operating temperature for servers typically ranges between 18°C and 27°C [27]. To ensure uninterrupted functionality, the server was placed in a shielded location away from wet, dusty, or extreme temperature fluctuations. Data transmission from the barn to the server is facilitated through PLC and RTSP protocols. The server processes the collected temperature and image data and relays the results to the artificial intelligence model. The AI model analyzes these inputs and distributes actionable insights to system components, enabling efficient decision-making and execution of barn climate control strategies.

2.4. Methods

The system identifies image and temperature data, transferring them sequentially to the PLC and server through various communication protocols. These data are supplied as parameters to the AI model hosted on the server. The model processes the inputs to make decisions, which are subsequently transmitted back through the server and PLC to control the barn cooling systems. This closed-loop mechanism transforms the system into an intelligent, automated entity. The system comprises various elements meticulously determined through experimental evaluations, ensuring optimal functionality under challenging barn conditions. By integrating these components, the system achieves seamless communication, precise decision-making, and efficient execution of climate control strategies.

- Programmable Logic Controller (PLC): In this study, a PLC is utilized to control the cooling systems (e.g., fans and sprinklers) based on data received from the AI-powered object tracking model. Additionally, it is used to transmit temperature data from the PT100 temperature sensor to the server. PLCs must be robust enough to withstand barn environments characterized by dust, humidity, and temperature fluctuations [28]. PLCs are essential components in industries with advanced machinery and devices primarily used for automation. They minimize human errors and interventions, ensuring safe, high-quality, and efficient production and control processes. These capabilities enhance system intelligence and efficiency. Frequently applied in ventilation and cooling facilities, PLCs are also suitable for barn climate control systems. Their simple programmability, ease of installation, operation, and maintenance, resilience in challenging environments, low failure rates, and reduced energy consumption make them an optimal choice. A basic diagram illustrating the operational principles of PLC systems is provided in Figure 3 to better understand the processes.

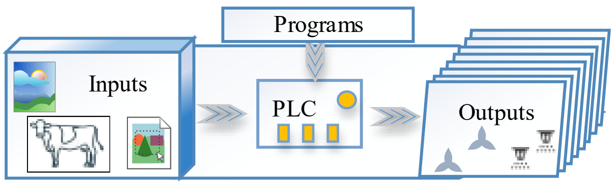

Figure 3. PLC operation diagram.

- Artificial Intelligence-Powered Image Processing Model: The system incorporates real-time image processing using the YOLOv10 deep learning algorithm, which is part of the YOLO family of image processing models. YOLOv10 is the latest and most advanced version, enabling simultaneous object detection and classification by analyzing an image in a single pass. Compared to its predecessors, YOLOv10 offers superior precision in object detection and classification [29]. The basic principle of the algorithm is dividing the input image into a grid and performing potential object detection within each cell. During this process, bounding boxes, dimensions, and probability scores for identified objects are generated. YOLOv10 further improves on earlier versions by employing advanced feature maps and architectural enhancements, enabling higher accuracy in detecting object boundaries and associating them with a confidence score. Its refined network architecture also significantly enhances its ability to detect objects of various sizes [30]. In this study, the model has been specifically adapted for monitoring dairy cows in barn environments. Raw images captured by cameras have a resolution of 2688x1520 pixels. Before feeding these images into YOLOv10, their resolution is adjusted to 1280x1280 pixels to ensure consistent data input for the algorithm. The algorithm is trained and validated using datasets containing cow images. Once trained, it can identify cows as objects and count their numbers within defined areas. Initially, the algorithm operates without spatial constraints, detecting all cows within the camera's field of view. As shown in Figure 4, the algorithm marks the position of each cow detected within the camera's range, providing location and classification data for integration into the cooling system [31]. This approach has been developed to enhance animal welfare and prevent unnecessary resource utilization, contributing to a more efficient and sustainable barn climate control system.

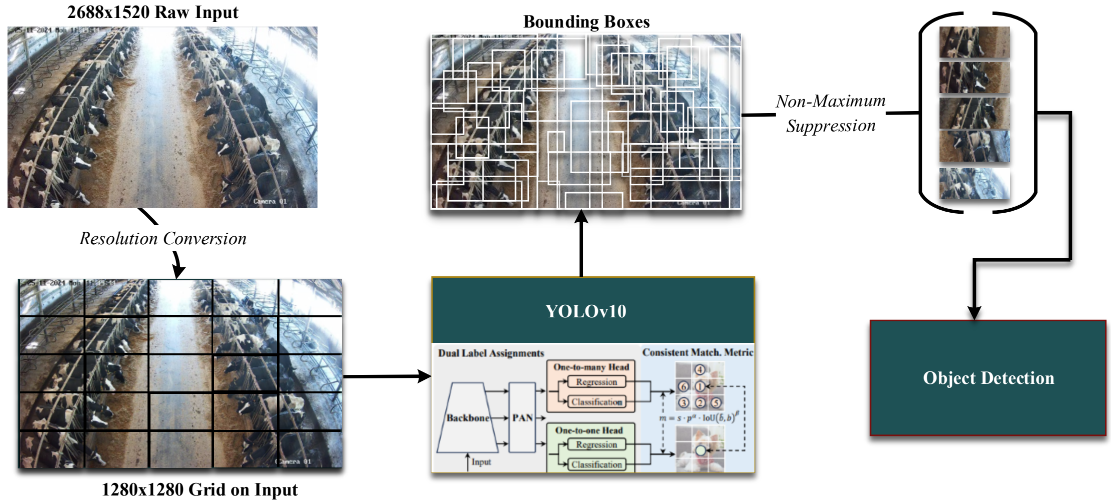

Figure 4. Visualization of YOLOv10 working mechanism.

2.5. Model Training and Evaluation

In this study, the object detection model used for real-time monitoring of dairy cows is based on the YOLOv10 architecture, a recent and advanced member of the YOLO family optimized for both speed and precision. A dedicated dataset was created using video recordings obtained directly from the experimental barn environment. In total, 6,400 image frames were extracted and manually annotated with the open-source tool LabelImg, where each cow was labeled using bounding boxes to define its spatial presence within the frame. To ensure proper evaluation and minimize the risk of overfitting, the dataset was divided into training 70%, validation 20%, and testing 10% subsets. During training, data augmentation techniques such as horizontal flipping, brightness variation, and random scaling were applied to improve the model's ability to generalize to different scenes and lighting conditions.

The training was performed using the PyTorch framework on a standard workstation without GPU support. Due to hardware limitations, the training process was optimized by adjusting parameters such as batch size (16) and learning rate (0.001). The model was trained for 100 epochs, and convergence was observed without signs of overfitting, supported by early stopping mechanisms based on validation loss trends. Model performance was evaluated using standard object detection metrics. Mean Average Precision (mAP@0.5) was used as the primary indicator of detection accuracy. Additionally, precision, recall, and F1-score metrics were calculated on the test dataset. The results, summarized in Table 1, demonstrate that the model achieved high detection performance and is suitable for real-time livestock monitoring in barn environments.

Table 1 presents the key training and evaluation parameters of the YOLOv10-based object detection model developed in this study. The table summarizes the dataset size, data split proportions, and critical hyperparameters such as batch size, learning rate, and training epochs. In addition, the table includes performance metrics such as mAP@0.5, precision, recall, and F1-score, all of which indicate that the model is capable of accurately detecting and tracking cows in real-time barn environments. These results confirm the model's suitability for integration into intelligent barn climate control systems.

Table 1. Training configuration and performance metrics of the YOLOv10-based object detection model.

Metric	Value
Dataset Size	6,400 images
Train/Val/Test Split	70% / 20% / 10%
mAP@0.5	91.2%
Precision	94.5%
Recall	89.3%
F1-Score	91.8%
Training Epochs	100
Batch Size	16
Learning Rate	0.001
Annotation Tool	LabelImg

3. Experimental Study

This study focuses on transforming barn climate systems into intelligent systems through the integration of an AI-supported image processing model for real-time control. The system leverages various methodologies to achieve this goal, with continuous monitoring of temperature and visual data. Visual data is captured using HIKVISION DS-2CD1643G0-IZS/UK cameras and transmitted to the system's server via the RTSP protocol over a network. Similarly, temperature data from the PT100 sensor is sent to the server through Modbus TCP protocol using a PLC. The server processes these inputs and passes them to the AI-powered image processing model.

The implemented system continuously collects data from sensors and cameras and transmits it to the model in real-time. Temperature data obtained from PT100 temperature sensors, and image data captured by cameras, are processed and evaluated by the model. The model processes and analyzes the collected temperature and image data, which generates intelligent decisions for system control and transmits them to the PLC via the server. The PLC then executes these decisions to manage barn climate control systems, such as sprinklers and fans, enabling real-time operation. When input data changes, the model adjusts its decisions, ensuring the system remains dynamic and responsive. The model determines the activation of fans or sprinklers and the priority sequence between these systems, ensuring efficient operation. Fans and sprinklers are not activated simultaneously to prevent water from sprinklers being displaced by fans, which could result in wet feed or water reaching unintended areas. Instead, either fans or sprinklers are activated depending on conditions, such as the number of cows within the sprinkler range, ensuring water is not wasted and fan operation is not unnecessarily halted. The system is designed to function according to these principles while being tailored to the barn's layout for enhanced functionality. Furthermore, its modular design allows for adaptation to various barn configurations, providing a versatile and efficient solution. Figure 5 illustrates the barn's top-down layout, showcasing the system's design flexibility and adaptability.

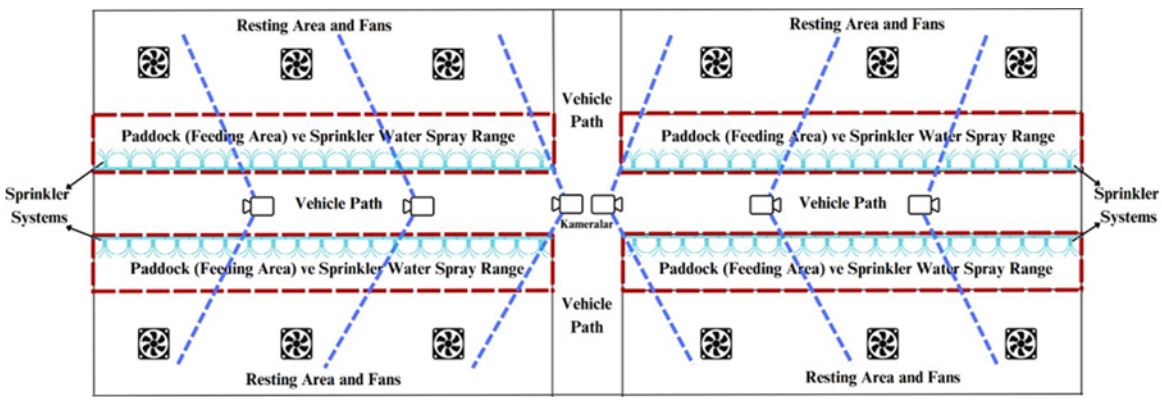

Figure 5. Bird's eye view of the barn where the work was conducted.

To enable the YOLOv10 deep learning algorithm to monitor dairy cows in the barn, the algorithm is pre-trained using datasets containing cow images and subsequently tested for accuracy. Once trained, the algorithm can recognize cows as objects and is utilized to determine the number of cows within a specified area. Initially, without any predefined area constraints, the algorithm detects all cows entering the camera's frame, as illustrated in Figure 6.

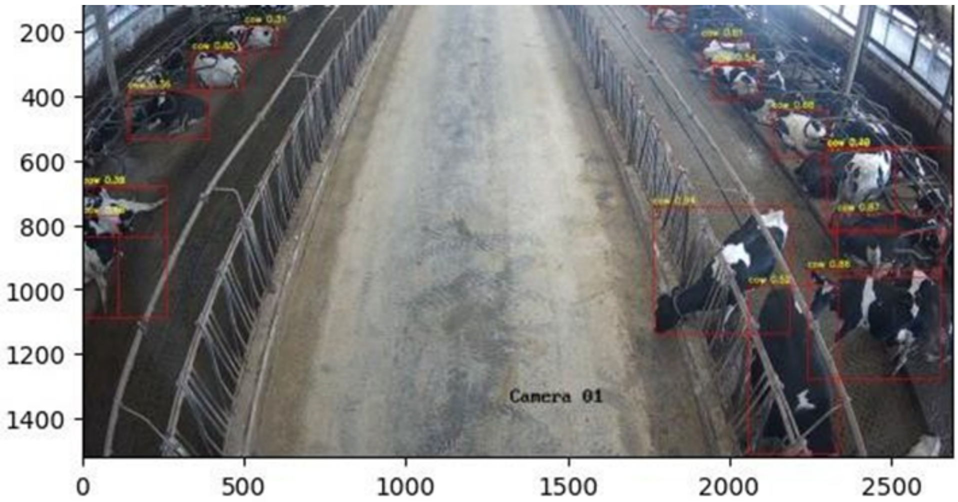

Figure 6. Image of cows detected using AI-Powered object detection.

In the subsequent stage, a restricted area is defined, encompassing only the feeding zones for the animals. To ensure object detection is confined to these specified areas, unique boundaries are set for each camera and the corresponding paddocks (feeding zones) they monitor. These restricted areas also represent the spray range of the sprinkler system. Defining these boundaries is crucial for determining the number of cows within the area. Each camera has distinct coordinates for these zones, making them unique to its view. Consequently, the system processes calculations and decisions independently for each camera. In a single barn, six cameras are installed, and each connects to the system via its IP address. The restricted areas for each camera are defined exclusively based on its field of view. Initially, footage from the cameras is reviewed, and a frame encompassing the desired area is drawn over the images. Points are then marked on this frame to define the unique boundary for each camera. These points represent the coordinates of the restricted area for each camera, forming a set of corner points that outline the region. As depicted in Figure 7, the green line illustrates the boundary of the restricted area, while the red dots denote the coordinate points marking the corners of the frame.

Figure 7. Camera-Specific frame lines and the coordinate points passed by the frame.

After defining the restricted area, it is integrated into the algorithm. Object detection is then carried out specifically within this zone in order to count the cows, as illustrated in Figure 8. By limiting detection to the designated area, the analysis becomes more precise and avoids unnecessary noise from irrelevant regions. To further enhance the interpretability of the image, the parts outside the defined zone are obscured with a dark blur, ensuring that attention remains focused only on the relevant area where detection is performed.

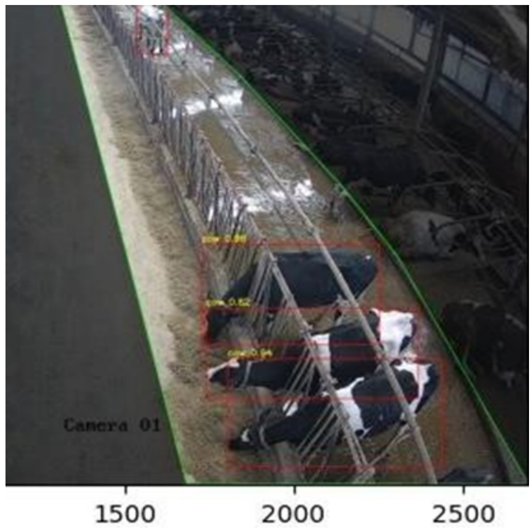

Figure 8. Counting cows using object detection within a defined area.

3.1. Evaluation of Data by the Algorithm and Sending Commands to Climate Control Systems

The algorithm makes decisions based on temperature data and the number of cows detected within the restricted area captured by the relevant camera. If the number of cows within the restricted area exceeds a predefined threshold, specific commands are transmitted to the barn cooling systems via the server and subsequently through the PLC. For instance, if the threshold is set to 10, the condition is met when the count of cows is 10 or more. Upon meeting this condition, the sprinkler system is activated based on the model's decision, ensuring that water is sprayed only when a sufficient number of cows are present in the area, thereby cooling them effectively. If the required number of cows is not present in the area, the sprinkler system remains inactive, reducing water usage. Furthermore, when the sprinkler system is not activated, the fans continue to operate, preventing unnecessary interruptions in their operation.

Another parameter considered by the model is temperature data, which is included to ensure the system is activated only when ambient temperatures exceed specific thresholds. Since the system aims to enhance animal comfort while optimizing efficiency and resource usage, it remains inactive when temperatures are low, reducing resource consumption. For instance, the temperature threshold for activating fans can be set at 17°C, while sprinklers may require a threshold of 22°C. If the conditions are met—for example, when the temperature rises to 17°C or higher— fans are activated. However, for the sprinklers to operate, both temperature and cow count parameters must satisfy their respective conditions. For instance, if the temperature is 22°C or above and the number of cows is 10 or more, the sprinklers are activated, and the fans are deactivated. Additionally, the sprinkler system's activation duration is predefined based on research and experimental findings, ensuring minimal water usage while maximizing efficiency. Once the specified time has elapsed, the system is automatically deactivated through a command sent by the algorithm, preventing unnecessary resource usage and ensuring optimal performance.

Furthermore, the algorithm's activation thresholds, such as a minimum cow count of 10 or a temperature value of 17°C, can be modified and updated via the interface used for managing and monitoring the PLC. These adjustable activation parameters enable real-time control and customization to suit varying operational requirements. As shown in Figure 9, the PLC interface allows for seamless updates and revisions of these thresholds, ensuring the system remains adaptable and efficient in responding to dynamic environmental and operational conditions.

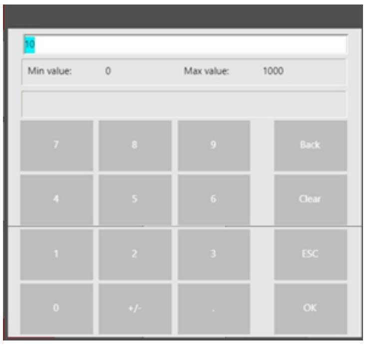

Figure 9. Cow number lower value or temperature lower value update screen image via PLC Interface.

Finally, the system operates with two different modes, which can be switched via the PLC interface. These modes are: manual and automatic (where the climate control systems are managed by the artificial intelligence model). In manual mode, both the sprinkler and fan systems can be controlled individually, allowing for manual activation or deactivation of the selected climate control components. This operational feature makes it easier to turn the system on or off when necessary. For instance, during system maintenance or when veterinary professionals need to inspect the animals, the system can be turned off. Figure 10 illustrates the changes that can be made through the PLC interface and the information that can be monitored.

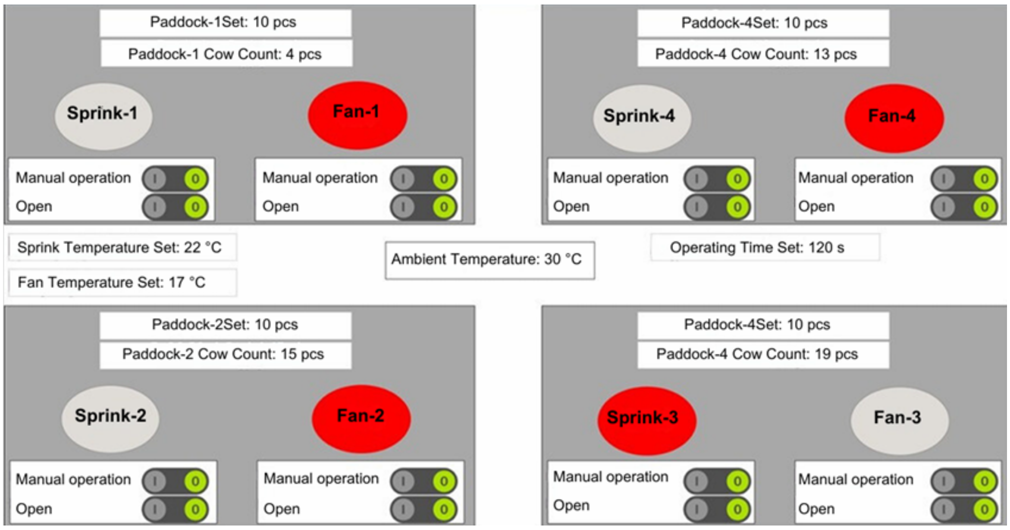

Figure 10. PLC ınterface screen.

Through the PLC interface, real-time temperature data, the temperature threshold required for the activation of the fan, the temperature threshold required for the activation of the sprinklers, information on which system (fan or sprinkler) is currently operating in the respective barn section, the required number of cows for the sprinkler system to activate in that section, the number of cows in the padlock area (within the restricted area or sprinkler system range) in that barn section, and the duration for which the sprinkler system will operate can all be accessed. This interface allows the system to be monitored remotely.

4. Results

4.1. Electromotive Force Effects and Diode Implementation

In the barn climate control system, the sprinkler systems are controlled by solenoid valves, which regulate water flow. Solenoid valves are electromechanical components that convert electrical energy into mechanical energy. They are used in the control of fluids such as water, gas, and oil. During the opening and closing of the solenoid valve, a phenomenon known as "counter-electromotive force" (back EMF) is generated. This is due to the coil inside the valve, which acts as an inductor. When current passes through the coil, magnetic energy is stored, and this energy can create voltage spikes that are high enough to damage sensitive circuit components. This issue can disrupt the proper functioning of the system and has the potential to cause damage to system elements and lead to additional costs. This problem was identified during operation and was proactively addressed. To resolve this, it is necessary to protect the circuit components from the high voltage spikes caused by back EMF. Diodes, which are circuit elements used to protect against such spikes, were employed. Diodes are used in electronic circuits to block current in an unwanted direction [32]. With the use of diodes, the instantaneous reverse current was blocked, making the system more reliable and efficient. When a diode is added to the circuit in the direction of current flow, it prevents current from flowing in the opposite direction.

4.2. Effects of Power and Internet Interruptions on the System

In hot summer days, power and internet outages can disrupt the system's operation. Power outages can be avoided using electrical generation tools such as generators available at the facility. However, internet outages hinder the correct operation of the model because data transmission and communication between system components are facilitated via internet protocols. In the case of network failures, the system must have a structure that can tolerate such situations. This ensures that the system is minimally affected by interruptions. In the event of network issues, data should be backed up across different virtual machines to ensure that the connection remains sustainable. This approach helps build a fault-tolerant system [33]. If the internet outage persists for a long period, the system should deactivate itself, and the barn climate control components should remain in a continuous working state to protect itself. This is because extended outages, lasting several days, may result in situations such as failure to detect and monitor faults and the depletion of virtual machines' storage capacities. This continuous operation of the climate control systems follows the old operating principle until the internet connection is restored. Therefore, even during an internet outage, the system will continue to operate in some capacity.

4.3. Real-Time Object Detection of the System

Unlike traditional barn systems, the preference for climate control systems managed by a real-time, AI-powered end-to-end object detection model offers significant advantages to businesses by reducing the use of resources such as labor, water, etc., through real-time operation. YOLOv10 is the tenth version of the object recognition algorithm. This algorithm allows for real-time object detection by processing frames at a high rate per second. Since real-time tracking provides advantages such as instant data generation and processing, it ensures that the system operates with the principle of a dynamic mechanism [34]. With this real-time tracking, businesses can reduce resource usage, allowing for continuous production. The use of intelligent systems eliminates the need for constant human control, lifting a significant burden on the business. Additionally, the real-time data processing and decision-making mechanism enable the climate control systems of the business to respond with variable actions to changing conditions, ensuring stable livestock production and maintaining their welfare. This results in a live and dynamic system.

4.4. Effects of Data Generation on the System

In contrast to traditional systems where data production and analysis are not typically involved, the implemented intelligent system ensures continuous data production and analysis. This is important as it allows for the development of new outcomes and observations that benefit the business through the generated data. A system that produces data holds significant potential for the development of additional features and the execution of future studies. For instance, the generated data could be utilized in future research related to animal health and psychology.

4.5. Importance of Regional Control in the Barn

Within the scope of the study, the developed system was also evaluated in terms of its ability to monitor different regions of the barn separately. This regional control made it possible to track animal behaviors and movement patterns in specific areas. During the observation process, the system successfully detected changes in activity density, especially in feeding and resting zones. In some cases, a noticeable reduction in movement was recorded in the rear sections, while increased clustering near feeding lines was also observed. These findings indicate that the model can provide useful information for early detection of irregularities and support faster intervention in region-specific issues.

4.6. Advantages of Using PLC

In the conducted study, an Arduino microprocessor, which is a more cost-effective device compared to a durable device like PLC, was initially used. However, the microprocessor was unable to fully optimize its function and could not respond adequately to the barn's conditions and the system's workload. As inefficient and unstable operation would pose a significant issue, a more robust and durable device, the PLC, was chosen to ensure stability, reliability, and optimization. Since the PLC also has a closed-loop structure, it is far more resilient to damage in the harsh barn conditions and operates with better performance. Furthermore, although PLCs may appear more costly than some microprocessors initially, they remain a cost-effective option in the long run due to their lower maintenance costs and reliable operation.

4.7. Effect of Temperature on Milk Production

The data collected from the facility, when analyzed, yielded results similar to the literature information mentioned in the introduction. According to this finding, the increase in temperature negatively affects the milk production of the animals, which in turn leads to a decrease in the facility's profitability. As shown in the graph in Figure 11, after a certain temperature threshold, an inverse correlation is observed between temperature and milk production. When the correlation coefficient for this relationship was calculated, it came out to be -0.64. This value provides significant support for the hypothesis that there is an inverse relationship between temperature and average milk production. The correlation coefficient of -0.64 implies that there is a negative correlation between temperature and milk production, although this relationship does not hold true in all cases. According to the analysis results, temperature does not negatively affect milk production when it is within the optimal range for cows, but as the temperature rises significantly during the summer months, it negatively impacts milk production. Subsequently, the reliability of the correlation was assessed using a t-test. The t-test value was –66.18, indicating a strong statistical difference. In general, the larger the magnitude of the t-value, the greater the likelihood of a significant relationship between the variables. When the p-value was calculated, it came out to be 0.0, which indicates that the likelihood of the difference between temperature and milk production being due to random chance is very low. Since the p-value is smaller than 0.05 (the typical significance level), it was concluded that this correlation is statistically significant. Therefore, the t-value shows that these two variables are meaningfully different from each other, while the very low p-value indicates that the correlation is not random and is indeed statistically significant. The accuracy of the correlation was proven through the calculation of these values. As a result, this analysis highlights the importance of making barn climate control systems intelligent.

As illustrated in Figure 11, milk production remained relatively stable between approximately 0 °C and 15 °C, averaging around 34.5–35 kg per cow. However, once the temperature exceeded 20 °C, a gradual decline became evident. Particularly after 25 °C, the average milk yield dropped below 32 kg, and in the 32–33 °C range, it fell sharply to nearly 29 kg. This clear inverse pattern supports the statistical findings and demonstrates the temperature sensitivity of dairy production. In conclusion, the results of the study confirm that rising temperatures negatively affect milk production. This finding underscores the importance of using barn climate control systems to protect animal welfare and ensure productivity. While this study did not directly measure the performance of intelligent systems, the strong and statistically significant correlation between temperature and milk yield highlights the potential value of more responsive, automated solutions. Future studies should investigate how smart control systems may contribute to energy-efficient operation and further improvements in milk production under varying environmental conditions.

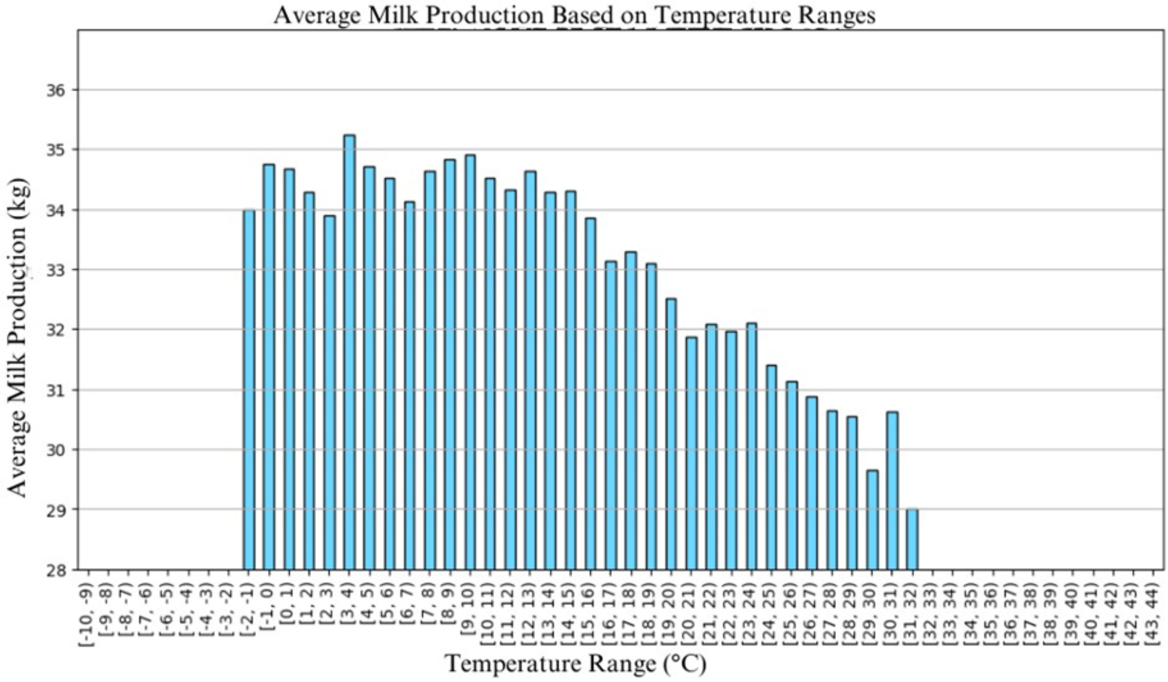

Figure 11. Average Milk Production by Temperature Ranges

4.8. Quantitative System Performance Evaluation

To complete the correlation analysis between temperature and milk production, various quantitative indicators of system performance related to the AI-based climate control system were also evaluated in the study. These quantitative indicators include the system's response time to trigger conditions, water usage efficiency encountered during the test period, and finally, the performance achieved in object recognition while detecting cows.

To determine the system response time, the average time between the detection of a trigger condition (e.g., reaching the cow number threshold and temperature threshold) and the activation of the relevant climate control component (sprinkler or fan) was measured. The system showed an average response delay of 1.8 seconds, which is acceptable for real-time operations in barn conditions. A comparative analysis was conducted between the traditional timer-based sprinkler system and the AI-assisted decision system over a 10-day test period to determine whether there was efficient water usage. The AI-based system achieved a 28% reduction in total water consumption while maintaining similar or better animal comfort levels. This demonstrates the system's capacity to effectively optimize resource usage and provides an advantage in terms of efficiency. Another indicator, cow detection accuracy, as detailed in Section 3.1, the YOLOv10-based object detection model achieved 91.2% mAP@0.5 with 94.5% sensitivity and 89.3% recall. These figures validate the model's ability to accurately detect and count cows in restricted areas in real time, ensuring correct system activation according to the actual animal presence.

These quantitative results show that the system not only conceptually improves barn operations, but also provides measurable gains in terms of responsiveness, resource efficiency, and detection accuracy. Such results are important to validate the applicability of the model in practical, real-life farm environments.

5. Discussion

The transformation of traditional barn climate control systems into intelligent and automated structures represents an important step in modern livestock management. This was made possible by integrating image processing technology supported by artificial intelligence. Throughout the integration process, different methods were tried, and some adjustments were made as needed to improve performance. Barn ventilation and climate control systems serve two main purposes: protecting animal welfare and ensuring the durability of barn equipment. Maintaining a stable environment for animals also helps prevent damage to equipment. The system developed in this study addresses both goals by enabling automated, real-time monitoring and environmental regulation. One significant advantage is the system's ability to produce and process data, something the previous setup could not do. This feature provides valuable insights that may guide future improvements. Also, the system allows remote access to real-time data, helping users manage the barn environment more efficiently. While no critical disadvantages were observed during the study, a few technical limitations emerged. The system relies on a stable internet connection to activate AI-based decision-making. Although basic operations continue during outages, extended disconnections can prevent smart functions from working. In addition, harsh barn conditions such as humidity and dust posed challenges for electronic components. To address this, durable, water- and dust-resistant equipment was used, and protective measures were implemented. Voltage spikes caused by sprinkler valve activity were resolved with diodes to stabilize the system.

Several studies in the literature support and align with the approach taken here. Rebez et al. [35] examined how AI-based tools can manage heat stress in ruminant animals, showing that real-time behavioral monitoring helps reduce productivity losses. Li et al. [36] investigated air conditioning (AC) and evaporative cooling (EC) systems, finding that AC systems offered better thermal comfort and could reduce energy consumption by up to 73%, even though their initial costs were higher. Macovoray et al. [37] tested different sprinkler flow rates and timing strategies. Their results showed that a 1.25 L/min flow rate using a 3|3 on/off cycle conserved 37.2% more water without lowering milk production. Similarly, SyNguyen-Ky and Katariina Penttilä [38] improved the effectiveness of natural ventilation systems in cold climates by calibrating energy models with long-term data. Another study on the effects of climate change on animal health found that heat stress negatively impacts milk yield and reproductive performance, and recommended the adoption of modern control systems and resilient breeds as a response [39].

These studies all point to the growing role of smart and adaptable technologies in livestock farming and support the approach taken in our study. Our system builds on these findings but offers a more integrated solution. Unlike the systems above, which are often static or manually operated, this model includes dynamic activation based on both environmental inputs and cow presence. It doesn't just apply cooling on a timer—it responds to real-time needs. While the system does not address every challenge related to barn climate management, it demonstrates that targeted improvements through practical and adaptive design can yield meaningful results. Taken together, these findings show that adapting climate control systems to real-time data and environmental variability is not only possible, but increasingly necessary. The results of our work contribute to this evolving landscape and highlight how smart, responsive systems can support more resilient and efficient livestock farming practices. Future studies may explore the implementation of this system in barns of different sizes, animal breeds, and geographic locations. Additionally, integrating predictive analytics or adaptive control mechanisms may enhance the system's responsiveness. The model's architecture also opens opportunities for application in other areas of precision agriculture, such as automated feeding or health monitoring systems.

6. Conclusion

In this study, an AI-powered smart cooling system was developed to address heat stress in dairy cattle, a growing concern due to climate change. By integrating real-time object detection and data processing models into barn operations, the system enables automated, adaptive control of cooling mechanisms based on actual animal presence and environmental conditions. Unlike conventional systems, which rely on static timers, the proposed system responds dynamically-activating cooling only when necessary and optimizing resource use. Experimental results confirmed the system's high performance: it achieved an average response time of 1.8 seconds, a 28% reduction in water consumption, and an object detection accuracy of 91.2% mAP. Additional metrics such as precision (94.5%), recall (89.3%), and an F1-score of 91.8% further validate the robustness of the model under real-world barn conditions.

These findings demonstrate that the integration of artificial intelligence and image processing can significantly improve operational efficiency, reduce environmental impact, and enhance animal welfare in livestock facilities. Moreover, the transformation of traditional infrastructure into intelligent, data-generating systems represents a meaningful step toward sustainable and precision agriculture. Future work may focus on adapting this framework to different species, expanding its functionality under diverse environmental conditions, and incorporating renewable energy or IoT-based scalability for broader agricultural applications.

Author Contribution Statement

The primary author led the conceptualization of the study, initiating the development of its core idea. All authors contributed equally to the workload, including the study's design, data collection, analysis, and critical revisions. The collaborative effort ensured that each author played a significant role in shaping the manuscript, from its initial drafting to its final form, maintaining scholarly rigor and intellectual integrity throughout the process.

Ethics Committee Approval and Conflict of Interest Statement

No ethical approval was required for the preparation of this manuscript. There are no conflicts of interest with any individual or institution related to the preparation of this manuscript.

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