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Robotics Systems and Artificial Intelligence Applications in Livestock Farming

Hayvancılıkta Robotik Sistemler ve Yapay Zekâ Uygulamaları

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ABSTRACT

Livestock farming, as a part of agriculture, has been an activity for centuries aimed at meeting the basic food needs of humans. This sector includes various sub-branches such as cattle farming, small ruminant farming, poultry farming, and beekeeping. Traditionally, animal care and production, carried out by human labour, have begun to be supported by technologies such as machines and artificial intelligence with the advancement of technology. Innovations such as artificial intelligence applications, image processing systems, and autonomous farm systems have reduced human errors and increased quality and speed in production. Especially in cattle farming, robotic systems and artificial intelligence applications reduce labour costs, increase productivity, and minimize environmental impacts. In the future, with more advanced robotic systems and artificial intelligence algorithms, the livestock industry will become more sustainable. These technologies have also been effective in areas such as disease detection. Specifically in cattle farming, it has been emphasized that robotic systems and artificial intelligence applications reduce labor costs, increase productivity, and minimize environmental impacts. It is predicted that in the future, with more advanced robotic systems and artificial intelligence algorithms, the industry will become even more sustainable. The use of robotic systems and artificial intelligence applications in the cattle farming industry brings a variety of benefits. These technologies reduce labour costs, increase efficiency, improve animal welfare, and minimize environmental impacts. Additionally, they enable the production of healthier animals and higher quality products. The cattle farming industry will continue to undergo significant changes with the further proliferation of robotic systems and artificial intelligence applications. In the future, more advanced robotic systems and artificial intelligence algorithms will further optimize cattle farming processes and make the industry more sustainable. Robotics systems and artificial intelligence applications are driving a significant transformation in the cattle farming industry.

Keywords: Livestock, Farm Systems, Artificial Intelligence Applications, Autonomous Technologies, Image Processing, Robotic Systems.

ÖZ

Hayvancılık, tarımın bir parçası olarak insanların temel gıda ihtiyaçlarını karşılamak amacıyla yüzyıllardır var olan bir faaliyettir. Bu sektörde büyükbaş, küçükbaş, tavukçuluk ve arıcılık gibi farklı alt dallar bulunmaktadır. Geleneksel olarak insan gücüyle yapılan hayvan bakımı ve üretimi, teknolojinin ilerlemesiyle makineler ve yapay zekâ gibi teknolojilerle desteklenmeye başlamıştır. Yapay zekâ uygulamaları, görüntü işleme sistemleri ve otonom çiftlik sistemleri gibi yenilikler, insan hatalarını azaltarak üretimde kalite ve hız artışı sağlamıştır. Özellikle sığır yetiştiriciliği alanında robotik sistemler ve yapay zekâ uygulamaları, işgücü maliyetlerini düşürmekte, verimliliği artırmakta ve çevresel etkileri minimize etmektedir. Gelecekte daha da gelişmiş robotik sistemler ve yapay zekâ algoritmalarıyla hayvancılık endüstrisi daha sürdürülebilir bir hale gelecektir Bu teknolojiler, hastalık tespiti gibi alanlarda da etkili olmuştur. Sığır yetiştiriciliği özelinde, robotik sistemlerin ve yapay zekâ uygulamalarının işgücü maliyetlerini azalttığı, verimliliği artırdığı ve çevresel etkileri minimize ettiği vurgulanmıştır. Gelecekte, daha da gelişmiş robotik sistemler ve yapay zekâ algoritmalarının endüstriyi daha sürdürülebilir hale getireceği tahmin edilmektedir. Robotik sistemlerin ve yapay zekâ uygulamalarının sığır yetiştiriciliği endüstrisine bir dizi faydası vardır. Bu teknolojiler, işgücü maliyetlerini azaltır, verimliliği artırır, hayvan refahını iyileştirir ve çevresel etkileri minimize eder. Ayrıca, daha sağlıklı hayvanlar ve daha yüksek kaliteli ürünler elde edilmesine olanak tanır. Sığır yetiştiriciliği endüstrisi, robotik sistemlerin ve yapay zekâ uygulamalarının daha da yaygınlaşmasıyla önemli değişikliklere tanık olmaya devam edecektir. Gelecekte, daha gelişmiş robotik sistemler ve yapay zekâ algoritmaları, sığır yetiştiriciliği süreçlerini daha da optimize edecek ve endüstriyi daha sürdürülebilir hale getirecektir. Robotik sistemler ve yapay zekâ uygulamaları, sığır yetiştiriciliği endüstrisinde önemli bir dönüşüm sağlamaktadır.

Anahtar Kelimeler: Hayvancılık, Çiftlik Sistemleri, Yapay Zekâ Uygulamaları, Otonom Teknolojiler, Görüntü İşleme, Robotik Sistemler

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INTRODUCTION

The livestock sector plays a significant role in meeting the increasing demand for food due to the growing population. However, to meet this demand, it is necessary to increase efficiency and utilize resources more effectively. Technological innovations, particularly robotic systems and artificial intelligence (AI), have the potential to revolutionize livestock farming by enhancing productivity, improving animal welfare, and supporting environmental sustainability. Robotic systems are utilized in various areas of livestock farming. For example, automatic milking machines increase milk productivity while ensuring the comfort of animals. Feeding and watering systems automatically fulfil the nutritional and water needs of animals, minimizing human errors. Additionally, herd management and monitoring systems are used to monitor the health status, track movements, and provide data to farm managers. Artificial intelligence finds numerous applications in the livestock sector. For instance, AI models used to monitor and predict animal health have the potential to detect diseases early and improve treatment processes. Furthermore, AI algorithms for nutrition and genetic optimization can enhance animal productivity. The benefits brought by robotic systems and AI applications in the livestock sector include increased productivity and profitability, reduced human errors, and mitigated environmental impacts. However, challenges such as investment costs and accessibility to technology need to be addressed. Additionally, societal acceptance and regulatory barriers are important factors to consider. In the future, the widespread adoption of artificial intelligence and robotic systems in livestock farming is expected. With the emergence of smarter and automated farms, greater efficiency and sustainability will be achieved in the livestock sector. However, further research and development efforts are needed to effectively implement these technologies. Robotic systems and artificial intelligence applications in livestock farming represent promising technologies for the future of the sector.

Artificial intelligence is present in many aspects of our lives, capable of observing and performing tasks, calculations, and detections that would otherwise require human intervention. It is commonly used in agriculture, livestock farming, the medical sector, manufacturing, logistics, aviation, spatial design, and various other fields. The foundation of artificial intelligence lies in philosophy and was later mathematically modeled. Throughout history, renowned figures such as Aristotle (384–322 BC) mentioned automatons in his book "Politics," followed by the works of scholars like Al-Jazari and Leonardo da Vinci. Alan Mathison Turing, who raised the question "Can machines think?" during World War II in 1943, is considered the father of artificial intelligence. Artificial intelligence has evolved from being a concept or dilemma to generating alternative solutions through mathematical models. It encompasses subfields such as machine learning, deep learning, natural language processing, pattern recognition, genetic algorithms, expert systems, speech recognition, robotics, computer vision, and optimization, each focusing on producing solutions for different problems.

Throughout history, humans have relied on agriculture and livestock farming to meet their basic food needs, sustaining generations with harvested crops and livestock products. Artificial intelligence has also entered the livestock farming sector with the aim of minimizing potential issues resulting from human error. It is expected to efficiently perform tasks with minimal costs under optimal conditions. Artificial intelligence is utilized in various aspects of livestock farming, including disease diagnosis, daily routine care, collection of products, improvement of welfare levels, and monitoring of breeding needs.

This study will explore the applications of artificial intelligence and robotic technologies in livestock farming. It will discuss the use of machine learning, deep learning, and fuzzy logic, which are branches of artificial intelligence, with a focus on future unmanned animal farms.

ARTIFICIAL INTELLIGENCE

Artificial intelligence is present in many aspects of our lives. It is capable of observing operations, calculations, and detections that would be done with human intervention. It is frequently used in fields such as agriculture, animal husbandry, the medical sector, manufacturing, logistics, aviation industry, space design, and design. Artificial intelligence is rooted in philosophy. It was later modelled mathematically. In history, Aristotle mentioned automata for the first time in his book "Politics" [Tuncay,2019). In the following years, the works of famous philosophers such as Al-Jazari and Leonardo da Vinci, who dealt with the philosophy of science, continued. Alan Mathison Turing, who raised the question "Can machines think?" during World War II in 1943, is considered the father of artificial intelligence (Hodges ,2014). In the following years, artificial intelligence has evolved from being an idea or a problem into generating alternative solutions with mathematical models. Artificial intelligence is divided into subfields such as machine learning, deep learning, natural language processing, pattern recognition, genetic algorithms, expert systems, speech recognition, robotics, computer vision, and optimization, each focusing on generating solutions for different problems.

"In order for operations to take place, inputs and outputs are required. Inputs are processed through algorithms to obtain outputs (Süslü,2019). Artificial intelligence should have the ability to interpret these input data, make inferences, learn, and adapt to specific goals to perform desired tasks (Kaplan and vd,2019). Artificial intelligence is divided into many categories. Machine learning, deep learning, and fuzzy logic are some of them. Artificial intelligence optimizes functions that maximize the success of goals by analysing input data. For meaningful results to be derived from the data, it must be clean, organized, and consistent (Pirim,2006). This is why it works alongside data science (Hoehndorf and vd. 2017). There are many subfields of artificial intelligence, each with its own unique problem-solving methods. However, they share a common goal, which is to solve problems with maximum success using the available data.

Throughout history, hundreds of scientists have worked on this subject. New methods and techniques have been developed, expanding the pool of problem-solving approaches. In our study, we will examine the methods used in the literature. We will look at research on livestock farming that utilizes artificial intelligence in conjunction with other technologies to meet our basic needs.

MACHINE LEARNING and DEEP LEARNING APPLICATION

Machine learning and deep learning can be considered as subfields of artificial intelligence. Machine learning uses training data to determine the model that maps inputs to outputs using algorithms to obtain outputs from inputs (Süslü,2019).

Upon reviewing the literature, it has been observed that there are numerous studies related to livestock farming. These studies have been examined, and they include:

Tabak et al. (2019) conducted a study in which they automatically classified wildlife species from camera trap images taken in five states in the United States (US). The ResNet-18 architecture was used in the study. The model was trained with 3,367,383 images, and it achieved a 98% accuracy rate with images obtained in the US.

Valdes-Donoso et al.; investigated animal movements in 34 counties in Minnesota, US. The authors used a random forest algorithm to predict movements between two pig production facilities, farms, and markets. As a result, 286 and 215 animal movements were identified from the two production facilities, respectively. Only 14% of the movements were found to be related to fields in other counties;(Valdes-Donoso *et al*,2017).

Jensen et al (2016) aimed to detect cases of mastitis in cows. They used data from seven sensors along with a multivariate dynamic linear model (DLM) and Naive Bayes (NB) classifier. By modeling data such as milk yield, fat, protein, lactose, conductivity, blood, and body weight, the next sensor data was predicted using DLM. The probability of a cow having mastitis was combined with other cow-related data (season, week in milk, mastitis history, somatic cell count category, and parity) using Bayes' theorem. If this probability was above a certain threshold, the cow was classified as positive for mastitis. Data from 1,003,207 milking sessions collected between 2008 and 2014 were used. The DLM/NB method achieved a sensitivity of 80%, specificity of 81%, and an area under the receiver operating characteristic curve (AUC) of 89%.

Ebrahimi et al.; aimed to detect mastitis disease using a model developed on 364,239 milking data. Deep learning, naive Bayes, generalized linear model, logistic regression, decision tree, and gradient boosted trees (GBT) were used in the study. GBT achieved the highest performance with an accuracy rate of 84.9% (Ebrahimi et al,2019).

Yıldız (2016) used artificial neural networks to predict estrus in animals using pedometer data. A total of 186 estrus data were obtained from 78 cattle. The two-layered artificial neural network designed by the author achieved the highest performance with a ROC score of 0.9733.

Shahriar et al (2016) determined activity levels in large animals using inclinometer and temperature data. The main purpose of the study was to detect estrus in animals. They used the k-means algorithm for data clustering and achieved 100% sensitivity using methods such as identifying changes in the index. The study achieved an overall accuracy rate between 82% and 100%.

Brunassi et al. (2010) aimed to classify 25,000 estruses data. The study had a total of three classes, and an 84.2% sensitivity score was achieved.

Işık and Güler (2009) detected nipple damage in cattle after pressure differences in mobile milking machines using image processing techniques.

Debauche et al (2021) classified cattle face images using Faster Region-based Convolutional Neural Networks (FRCN). A total of 1579 images from 5 different cattle were used in the dataset. Training was performed with 1129 images, and testing was performed with 450 images. A 98.44% accuracy rate was achieved, and cattle face images were successfully classified.

Cihan et al (2017) performed decimal scaling, z-score, sigmoid, and minimum-maximum normalization on values in the dataset. The classification of disease diagnosis in lambs was done with artificial neural networks in the study. The highest performance F-measure was obtained with a sigmoid normalization of 0.36.

Rao et al (2020) developed a farm welfare monitoring system for goats using technologies such as machine learning and the Internet of Things (IoT). The system collects videos and images to monitor goat growth, allow remote control and maintenance, and analyze goat behavior. Support vector regression (SVR) and k-nearest neighbor algorithms were used. The system predicts temperature, humidity, and gas values with a high accuracy rate of 94% to 97.5%.

Volkmann et al (2021) proposed a method for detecting claw lesions by analyzing the acoustic analysis of cow walks. The random forest algorithm was used. A total of 640 sound files were collected from 64 cows. As a result of the study, an 81% sensitivity and a 97% specificity rate were achieved.

Raksha and Surekha (2020) used machine learning models such as k-nearest neighbors (KNN), logistic regression, and support vector machines (SVM). An Internet of Things (IoT)-based farm monitoring system was proposed in the study. As a result, SVM had the highest performance rate with.

Machine Learning and Livestock Farming

Machine learning and deep learning are subsets of artificial intelligence that play crucial roles in various fields, including livestock farming. Machine learning involves using training data to develop models that can map inputs to outputs through algorithms. These models are then used to generate outputs based on new inputs (Süslü, 2019).

Upon reviewing the literature, it becomes evident that there is a significant body of research focusing on the application of machine learning techniques in livestock farming. One such study was conducted by Tabak et al. (2019), who aimed to automatically classify wildlife species from camera trap images captured across five states in the United States (US). In their research, they utilized the ResNet-18 architecture and trained the model with an extensive dataset consisting of 3,367,383 images. Impressively, their model achieved an accuracy rate of 98% when tested with images obtained from the US.

This study highlights the potential of machine learning techniques in addressing various challenges in livestock farming, such as wildlife monitoring and management. By leveraging advanced algorithms and large datasets, researchers can develop models capable of accurately classifying species, thereby aiding in wildlife conservation efforts and promoting sustainable agricultural practices. As such, the integration of machine learning technologies holds promise for enhancing efficiency and productivity in livestock farming while minimizing environmental impacts.

Machine Learning and Livestock Farming: A Continuing Exploration

Machine learning and its subset, deep learning, are integral components of artificial intelligence with vast applications across diverse fields, including livestock farming. These technologies harness the power of algorithms to process vast amounts of data and derive meaningful insights.

A notable area where machine learning techniques have been extensively applied in livestock farming is in species classification and monitoring. Tabak et al. (2019) conducted a pioneering study utilizing the ResNet-18 architecture to automatically classify wildlife species from camera trap images collected across different regions in the US. Their model, trained on a substantial dataset comprising millions of images, achieved an impressive accuracy rate of 98%.

The success of such studies underscores the potential of machine learning in revolutionizing wildlife management practices within livestock farming. By accurately identifying and monitoring wildlife species, farmers and conservationists can better understand ecosystem dynamics, mitigate human-wildlife conflicts, and implement targeted conservation strategies.Moreover, the application of machine learning extends beyond wildlife monitoring to various other aspects of livestock farming, including disease detection, yield prediction, and precision agriculture. By analyzing data from sensors, satellite imagery, and historical records, machine learning algorithms can identify patterns and trends, enabling proactive decision-making and optimizing resource allocation.As research in this field continues to evolve, advancements in machine learning hold immense promise for transforming livestock farming into a more efficient, sustainable, and environmentally friendly industry. By harnessing the power of data-driven insights, stakeholders can unlock new opportunities for innovation and address the complex challenges facing the agricultural sector.

Advancements in Machine Learning for Livestock Farming

Continuing our exploration of machine learning's role in livestock farming, it's evident that ongoing research and innovation are driving significant advancements in this field.Beyond wildlife monitoring, machine learning techniques are being increasingly applied to address a wide array of challenges in livestock management. For instance, researchers are developing models to predict disease outbreaks, enabling farmers to implement timely interventions and prevent potential losses. Additionally, machine learning algorithms are being utilized to optimize feed formulations, minimize resource wastage, and enhance animal nutrition, thereby improving overall herd health and productivity.

Furthermore, the integration of machine learning with IoT (Internet of Things) technologies is enabling the development of smart farming systems that provide real-time monitoring and control of livestock environments. By leveraging sensor data on factors such as temperature, humidity, and air quality, these systems can automatically adjust environmental conditions to ensure optimal comfort and welfare for animals.The potential of machine learning in livestock farming extends beyond individual farm operations to broader industry-wide initiatives. Collaborative research efforts are underway to develop predictive models for market demand, supply chain optimization, and sustainable agricultural practices. By leveraging data from across the supply chain, stakeholders can make informed decisions to maximize profitability while minimizing environmental impact. Looking ahead, the continued integration of machine learning and related technologies holds immense promise for transforming livestock farming into a more efficient, resilient, and sustainable industry. By embracing innovation and leveraging data-driven insights, stakeholders can address emerging challenges and unlock new opportunities for growth and prosperity in the agricultural sector.

Table 1. Comparison of machine learning algorithms in the literature.

Tablo 1. *Literatürdeki makine öğrenmesi algoritmalarının karşılaştırılması.*

Authors	Methods	Topics	Results
Tabak M. and friends	ResNet – 18	Automatic Classification of Wildlife Species	Accuracy: 98%
Jensen D. and friend	Multivariate Dynamic Linear Model (DLM) + Naive Bayes (NB)	Detection of mastitis Disease	Sensitivity: 80%, Specificity: 81%, and Receiver Operating Characteristic: 89%
Ebrahimi M.and friend	Deep Learning,Naive Bayes, Generalized Linear Model, Logistic Regression, Decision Tree, Gradient Boosted Trees	Detection of mastitis Disease	GBT achieved the highest performance with an accuracy rate of 84.9%
Yıldız K	Artificial Neural Network	Heat Prediction	0.9733 ROC
Shahriar ve friend	K-Means	Heat Prediction	%100 Sensitivity %82 with%100 Overall accuracy
Dandıl E. and friends	Faster Region-based Convolutional Neural Networks (Faster R-CNN)	Classification of Facial Images	%98.44 Accuracy rate has been obtained
Cihan P. and friends	Artificial Neural Networks	Disease Diagnosis in Lambs in the Study	The highest performance with an F-measure of 0.36 was achieved with sigmoid normalization
Volkmann N. and friends	Random Forest	Detection of Hoof Lesions	At the end of the study, a sensitivity of 81% and a specificity rate of 97% were obtained
Raksha R. ve Surekha P.	NN SVM Logistic Regression	Farm Monitoring System	At the end of the study, SVM achieved the highest success rate with 89.6%
Warner D. and friends	Random Forest Logistic Regression	Detection of Grazing, Limping, Ruminating, and Other Behaviors in Farm Animals	The highest AUC was determined to be 0.76. Sensitivity: 0.54, Specificity: 0.94

FUZZY LOGIC APPLICATIONS

Fuzzy logic consists of control and decision-making processes closely resembling human thinking patterns, using meaningful information (Chen and T. T. Pham ,2000). It is commonly used in automatic control systems, information systems, image recognition, and optimization (Altaş ,1999). Many fuzzy logic applications in the field of animal husbandry have been studied in the literature. Some of these studies are as follows:

Wade K. M. and colleagues (1998) developed a fuzzy logic-based decision support system. The system provides output decisions based on culling for lactation order, reproductive activity, and production index in dairy cows.

Strasser M. et al. (1997) developed a fuzzy logic-based system for detecting low-yield animals, aiming to minimize cost losses for farms.

Morag I. et al. (2001) designed a decision support system using fuzzy logic to determine feed quantities based on parameters such as body weight and milk yield. The system was observed to integrate with herd management programs.

Mehraban et al. (2012.) proposed a fuzzy logic-based method to find the quality of raw milk, considering physicochemical and microbiological aspects, achieving a success rate of 82.5%.

Kramer E. et al. (2009) employed a fuzzy logic-based classification method to classify mastitis and lameness in cows. However, the desired performance values were not achieved in this study.

Memmedova and Keskin (Memmedova and Keskin 2011) aimed to classify the last estrus values and estrus states of cows using a fuzzy logic-based classification method, achieving a 98% success rate.

De Mol R. M. and Woldt W. E. (2001) proposed a fuzzy logic-based system to classify milk yield, electrical conductivity, and animal activity measured by sensors to classify mastitis and estrus alerts, enabling automatic monitoring of cow conditions.

Cavero D. et al. (2006.) suggested a system to classify mastitis disease in cows entering the automatic milking system using fuzzy logic classification, achieving specificity values between 93.9% and 41.9%.

Zarchi H. A., Blanke M., and Jónsson R. I. (2009) used a fuzzy logic technique along with a statistical detector to classify estrus alerts. The study achieved sensitivity of 85.3%, specificity of 100%, and an error rate of 2.8%.

Santos S. et al. (2017) described a fuzzy logic-based decision support system called Sustainable Pantanal Farm to assess the sustainability of cattle farms.

Zaninelli M. et al. (2016) developed a new fuzzy logic model to observe the mammary health of goats, achieving sensitivity of 56% and specificity of 92% at a cutoff level of 0.9.

Zaninelli M. et al. (Zaninelli M. et al 2016) determined the potential for detection by monitoring the health status and electrical conductivity values online. A similar approach was applied to milk yield, achieving a sensitivity of 81% and specificity of 69%.

Harsani P., Mulyana I., and Zakaria D. (2018) conducted a goat search game using the A* algorithm and fuzzy logic. Fuzzy logic was used to determine enemy behaviors, while the A* algorithm was used to find the shortest path.

Zaninelli M. et al. (2015) proposed a fuzzy logic-based system using online electrical conductivity data from sensors. The system evaluated health conditions and milk quality, achieving specificity and sensitivity values of 73% and 81%, respectively, at a cutoff level of 0.7.

The Use of Fuzzy Logic-Based Decision Support Systems in Livestock Farming

Livestock farming has become a significant field for the integration of modern technologies to enhance productivity and optimize farm management. In this context, artificial intelligence techniques, particularly fuzzy logic-based decision support systems, are increasingly being utilized in livestock farming. In this article, we will explore the various applications of fuzzy logic-based decision support systems in the livestock sector and the benefits they provide.

Fuzzy Logic and Decision Support Systems: Fuzzy logic is a powerful tool for modeling and controlling systems that involve uncertainty and complexity. Decision support systems are software or systems that assist decision-makers by providing analysis and data-driven recommendations, thus facilitating the decision-making process. Fuzzy logic-based decision support systems are used in various applications in the livestock sector due to their ability to address uncertainties.

Application Areas and Example Studies:

- Prediction of Lactation Period and Reproductive Efficiency in Dairy Cattle: In a study by Wade et al., a fuzzy logic-based decision support system was developed to provide culling decisions based on lactation stage, reproductive efficiency, and production index in dairy cattle.
- Livestock Productivity and Disease Detection: Strasser and colleagues developed a fuzzy logic-based system for detecting low-performing animals, aiming to minimize cost losses on farms.
- Feed Management: Morag et al. developed a decision support system that determines the amount of feed based on parameters such as body weight and milk yield, demonstrating its integration with herd management programs.

Fuzzy logic-based decision support systems have been successfully used in various applications in the livestock sector. These systems assist in making effective decisions in the uncertain livestock environment and optimize farm management. However, further research and development are needed, especially for the wider adoption of these technologies and addressing implementation challenges on farms.

The Use of Robotic Systems in Livestock Farming

The livestock sector is experiencing significant transformations with the advancement of technology. One of these transformations is the use of robotic systems in livestock farming. In this article, we will explore how robotic systems can be used in the livestock sector and the benefits this usage brings to the industry. In the livestock sector, robotic systems can be employed in a variety of different tasks. For example, automatic milking machines can reduce the workload of dairy cattle breeders and optimize milking operations. These machines are equipped with sensors capable of identifying cattle and automatically performing the milking process. Additionally, robotic feeding systems can reduce labor and optimize feed distribution by automatically providing feed to animals.

Monitoring and treating the health status of animals can also be done using robotic systems. For instance, smart bracelets that monitor the movements of cows and detect potential health issues have been developed. Moreover, automatic veterinary robots can assess the health status of animals and administer specific treatments.Robotic systems can also be used to improve animal welfare. For example, automatic cleaning robots can enhance hygiene standards and provide comfort to animals by cleaning animal shelters. Additionally, automatic herd management systems can monitor the movements of animals and optimize social interactions within the herd.

The use of robotic systems in the livestock sector provides several benefits. Firstly, reducing labor and automating processes can increase the efficiency of operations and lower operating costs for businesses. Furthermore, by enhancing animal welfare, it enables the breeding of healthier and happier animals. Additionally, the utilization of robotic systems can contribute to making businesses more sustainable and environmentally friendly.

The use of robotic systems in livestock farming is bringing about significant transformation in the industry. These systems not only increase operational efficiency but also enhance animal welfare. In the future, it is expected that more advanced robotic systems will be more widely used in livestock farming, leading to a more sustainable and innovative industry.

When literature is reviewed, it is observed that many routine actions and problems in animal husbandry are addressed by these systems. Some of these studies are:

In the study by Butler D. and Bear C. (2012), an automatic milking system (AMS) is proposed for use on farms without the need for human intervention. Detailed data is recorded by the robot, focusing on the relationship between the stockman and the AMS to enhance milking routines and improve cow health and welfare.

Kounalakis T., Triantafylidis G., and Nalpantidis L. (Kounalakis T., Triantafylidis G., and Nalpantidis L (2019) utilized a robotic platform to create a dataset of images of weeds on dairy farms. They developed a weed recognition algorithm using deep learning and applied transfer learning to classify weed species from real data, proposing a system for weed classification.

Rossing W. and colleagues (1997) described robotic arms, teat cleaning devices, milking equipment, and stations in the Netherlands in 1996. They discussed increasing milking frequency from 2 to 3 times, resulting in a gain of 1000 kg of milk and the positive impact of robotic systems on farmers.

Hamrita T., Tollner E., and Schafer R. L. (2000) focused on the role and importance of robotics in agriculture, discussing advancements in controllers and sensors and attempting to create a vision for the future.

Orsini R. and colleagues (2021) provided information about the PFRLab research project funded by the Università Politecnica delle Marche. The project aims to ensure the sustainability of crop systems and food safety by establishing a precision agriculture robotics laboratory and implementing smart farming in a multidisciplinary structure.

Lauguico and colleagues (2019) highlighted concerns about food shortages due to the increasing world population and demand for food. They focused on vertical farming using a robotic arm, which is expected to be popular in cities and farms, simulating the research using MATLAB and Universal Robots.

Nguyen V. and colleagues (2017) analyzed robotic tools used in agriculture, considering the continuous development of robotic and sensor technology as promising for future studies.

Mundan D. and colleagues (2014) evaluated farms operating with robotic milking systems from an economic perspective, discussing challenges and opportunities. They focused on investing in robotic farm systems to eliminate labor costs, concluding that larger farms find robotic systems more attractive.

Hyde J. and Engel P. (2002) discussed the returns and costs of investing in robotic milking systems, using Monte Carlo simulation to estimate the income/expenditure values of an RMS.

Wagner-Storch A. and Palmer R. (2003) examined milk yield, nutrition, and milking behavior of cows milked using traditional methods versus robotic milking systems on a farm. Their study directly influences the design of transportation and feeding facilities for future automated milking systems.

Borshch O. and colleagues (2020) investigated indicators of adaptation of cows to robotic milking systems. The study was conducted on French Holstein, German Holstein, and Brown Swiss breeds in a robotic farm, observing that the German Holstein breed had a shorter adaptation period.

The livestock industry is undergoing profound changes propelled by technological advancements. One such transformation is the integration of robotic systems into livestock farming practices. This article delves into the applications of robotic systems in the livestock sector and the advantages they offer to the industry.Robotic systems find utility across various tasks within the livestock sector. For example, automated milking machines streamline dairy operations, alleviating the workload of cattle breeders while optimizing milking procedures. Equipped with sensors, these machines can identify cattle and autonomously conduct the milking process. Similarly, robotic feeding systems streamline feed distribution, reducing labour and ensuring efficient feeding practices. Monitoring and addressing animal health issues are other areas where robotic systems excel. Smart bracelets capable of monitoring cattle movements and identifying potential health concerns have been developed. Moreover, automated veterinary robots can assess animal health status and administer necessary treatments promptly. Robotic systems also play a vital role in improving animal welfare. Automated cleaning robots maintain hygiene standards in animal shelters, ensuring the comfort of livestock. Additionally, herd management systems monitor animal movements and optimize social interactions within herds, further enhancing animal well-being. The adoption of robotic systems in the livestock sector yields numerous benefits. By reducing labor and automating processes, operational efficiency is enhanced, leading to lower operating costs for businesses. Moreover, improved animal welfare results in the breeding of healthier and happier animals. Furthermore, the utilization of robotic systems contributes to the industry's sustainability and environmental friendliness. The incorporation of robotic systems into livestock farming represents a significant shift in the industry. These systems not only bolster operational efficiency but also elevate animal welfare standards. Looking ahead, the widespread adoption of more advanced robotic systems is expected to drive further innovation and sustainability in livestock farming.

The integration of robotic systems into livestock farming practices represents a significant advancement in the industry. Robotic technology offers a wide range of applications that enhance efficiency, productivity, and animal welfare. One area where robotic systems excel is in milking operations. Automated milking machines reduce the labor burden on farmers while ensuring consistent and hygienic milking processes. These machines are equipped with sensors that detect the presence of cows and adjust milking parameters accordingly. As a result, dairy farmers can optimize their milking routines and maximize milk production. Another key application of robotic systems in livestock farming is in feeding management. Robotic feeding systems accurately dispense feed to animals based on their nutritional needs, reducing waste and improving feed efficiency. By automating the feeding process, farmers can save time and resources while ensuring that their animals receive the proper nutrition. Robotic technology also plays a crucial role in monitoring animal health. Smart sensors and wearable devices can track vital signs and detect signs of illness or distress in livestock. Automated veterinary robots can administer treatments or medications as needed, providing timely care to sick or injured animals. In addition to improving efficiency and animal welfare, the use of robotic systems in livestock farming can also have environmental benefits. By reducing the need for manual labor and optimizing resource use, robotic technology can help minimize the environmental footprint of livestock operations.Overall, the integration of robotic systems into livestock farming represents a promising development for the industry. By harnessing the power of automation and artificial intelligence, farmers can improve their efficiency, productivity, and sustainability while ensuring the well-being of their animals. As technology continues to advance, the potential for innovation in livestock farming is virtually limitless.

CONCLUSION and RECOMMENDATIONS

When these studies are considered, it is understood that robotic systems address various routine actions and problems in animal husbandry. Especially automatic milking systems, weed recognition algorithms, the use of sensor technology, and robotic farming applications offer promising solutions to increase efficiency in animal husbandry and improve farm management. The results of these studies indicate the need for further research and development in the future. The broader adoption and integration of robotic systems in the livestock industry can provide significant benefits in terms of productivity and sustainability. However, some challenges such as the cost of technology, the complexity of animal behaviors, and environmental factors should also be taken into account. Therefore, it is important for future research to address these challenges and develop solutions to enable the more effective use of robotic systems in the livestock industry." The livestock sector is vital for meeting the growing demand for food due to population growth, but increasing efficiency is necessary. Technological innovations, particularly robotic systems and artificial intelligence (AI), offer significant potential to revolutionize livestock farming by improving productivity, animal welfare, and environmental sustainability. Robotic systems are utilized for tasks such as milking, feeding, and herd management, while AI finds applications in disease detection, nutrition optimization, and genetic analysis.

Artificial intelligence (AI) plays a crucial role in various sectors, including agriculture and animal husbandry. Rooted in philosophy and later developed mathematically, AI encompasses subfields such as machine learning, deep learning, and natural language processing. AI models analyze data to make predictions, learn from patterns, and optimize outcomes. These models require clean and organized data to generate meaningful results, often working in tandem with data science methods.

Machine learning and deep learning, as subfields of AI, have been extensively applied in livestock farming. Various studies have utilized these techniques for tasks such as wildlife species classification, predicting animal movements, and detecting diseases like mastitis. Machine learning algorithms like support vector machines (SVM) and deep learning architectures such as convolutional neural networks (CNN) have demonstrated high accuracy rates in tasks ranging from estrus prediction to milk yield monitoring.

Fuzzy logic, characterized by its ability to model complex systems with uncertainty, has found widespread application in livestock farming. Decision support systems based on fuzzy logic help optimize feed management, disease detection, and farm sustainability. These systems provide valuable insights for decision-makers by analyzing parameters like body weight, milk yield, and environmental conditions. Despite some challenges, fuzzy logic-based systems contribute significantly to improving productivity and decision-making in animal husbandry.

The integration of robotic systems and AI applications in livestock farming offers promising solutions to enhance productivity, animal welfare, and sustainability. While these technologies have demonstrated remarkable success in various studies, further research and development are needed to address challenges such as cost, complexity, and environmental factors. With continued innovation and adoption, robotic systems and AI will play a crucial role in shaping the future of the livestock industry towards greater efficiency and welfare oriented.

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