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SURVEY

Animal Behavior for Chicken Identification and Monitoring the Health Condition Using Computer Vision: A Systematic Review

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ABSTRACT Poultry farming needs to be productive and profitable if it is to help with food security issues like cost. To make money, economic management and the use of productivity standards like the Feed Conversion Ratio (FCR) calculation are essential. So, the best way to improve the performance of chickens is to use best management practices while they are growing. The paper also gives a broad overview of the vital ways in which recognized digital technologies are used to control the well-being of chickens. This review article gives a thorough look at the research, with a focus on sensor-based AI applications for analyzing chicken behavior and keeping track of their health. This study focused on the welfare of poultry because there are currently gaps in the literature regarding the development of universally accepted criteria for assessing poultry well-being and developing trustworthy monitoring strategies, most notably for the health of broiler chickens and the prevention of disease outbreaks. This paper is focused on the current condition of the smart farming and how to improve the smart farming sector using computer vision with IoT. The current and future operations for poultry management provide a huge opportunity for intelligent automation, which, if implemented, would make it possible to produce chicken that is both high-quality and affordable. As a result, this research provides a thorough analysis of the most cutting-edge Internet of Things (IoT) systems with Artificial intelligence (AI) capabilities as well as their most recent developments in the creation of intelligent systems in this field. The paper also explores the benefits and problems that AI and IoT provide for chicken farming.

INDEX TERMS Smart farming, computer vision, deep learning, machine learning, chicken detection and monitoring.

I. INTRODUCTION

Now a days, chicken meat is in increasing demand due to its high protein, low calorie, and low cholesterol content [1]. Yet, successful chicken production is contingent on a number of variables, including environmental circumstances, disease outbreaks, the breeding process, and efficient management procedures. To avoid infections, increase productivity, and assure the well-being of the broilers. This would allow for effective resource management and better decision-making, leading to increased productivity and lower costs. The AI-enabled IoT devices might significantly reduce expenses and assist poultry farm owners increase productivity [2].

Livestock farming is crucial to feeding the world's population, notably because of the prevalence of the chicken

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industry. By 2025, the value of the worldwide poultry market is projected to increase to 422.97 billion, a compound yearly growth rate of 7% [3]. It is arguable whether or not poultry farming is less harmful to the environment than cow farming because of the lower methane emissions, reduced resource requirements, and greater feed conversion ratios. The agriculture sector must enhance production quality and efficiency while protecting animal health and welfare in order to keep up with the rising demand for animal products [4]. This necessitates prioritizing the animals well-being and reducing their negative experiences, which may be difficult to quantify in large-scale farms. Consequently, it is essential to consider both the physical and emotional well-being of animals while trying to improve their welfare [5].

By 2027, the market for farm video surveillance systems is expected to reach US 3.6 billion. This will help farms keep up with growing demand, comply with bio-security laws, and get the most out of their animals [6]. In the last 20 years, remote monitoring, the use of sensors to collect physiological and behavioral data, the ability to store a lot of data, and the speed with which data can be sent have all improved [7], [8]. Before large-scale phenotype analysis can be carried out, there are still several technical obstacles that need to be conquered.

As the agricultural sector continues to grow, automated measurement systems are emerging as useful instruments for monitoring and promoting animal welfare. Nowadays, the agricultural sector, especially the poultry industry, is dealing with critical problems related to animal welfare [4]. The methods employed in modern poultry farming often lead to the untimely demise of chickens before they are fit for slaughter. Moreover, the egg industry commonly disposes of billions of male chicks, which are deemed unproductive, by killing and utilizing them as meat. These practices have sparked a growing concern about animal welfare and have given rise to demands for more humane and ethical approaches in the industry. Chickens with bruises, skin injuries, or other imperfections are often rejected at slaughterhouses due to poor meat quality in the poultry meat business [4]. Animal welfare, agricultural output, and the economy are all negatively impacted by this fatality rate. Increased mortality rates, diminished immunological function, and aberrant behaviors are only some of the welfare indicators that can be negatively affected by stresses and substandard living circumstances experienced by hens in their early lives. The tenderness, juiciness, and taste of chicken products can be affected by these factors. Furthermore, there may be adverse consequences on human health due to the presence of stress hormones in chicken products, such as an increased risk of heart disease and other chronic illnesses. That's why, to guarantee the production of high-quality and safe poultry products for human consumption, it's crucial to put hens' welfare at the forefront of the poultry business [7], [9]. The survival rate and quality of chickens grown in captivity have both been shown to improve with the use of cameras linked to artificial intelligence (AI) instrumentation systems to evaluate flocks for health concerns [4].

Farm animal welfare can be improved by catering to the specific needs of each animal as well as the collective requirements of the herd (flock). Improvements in sensors and instruments have made it possible to gather data on the individual animals' behavior, physiology, and production [10], [11]. Automatic monitoring devices in the poultry business have greatly benefited animal welfare by revealing previously unknown details about the habits and preferences of individual chickens. Producers can now make educated choices regarding poultry housing, feeding schedules, and other factors that affect animal welfare and output thanks to this data. Moreover, by standardizing data gathering and analysis, automated monitoring systems may cut down on labor expenses and boost productivity in the chicken business. Producers may learn more about their hens' tastes and habits with the help of these technologies, allowing them to maximize output without compromising on animal well-being.

Using computerized monitoring devices in the poultry sector is an exciting new trend that might improve life for hens and farmers alike [12], [13]. Since not all farm animals are evaluated in the same manner, this is essential information. Cattle and pigs, due to their larger size, more spherical bodies, and typically longer lifespans, provide for simpler individual monitoring than poultry [14]. Hence, automated monitoring devices can measure individual hens with the same accuracy, thanks to the use of artificial intelligence.

Some of the current technologies for tracking animal behavior include thermal imaging, implantable chips that record physiological information in real time, wearable sensors, and video recording. There are pros and cons to each monitoring method, and selecting one over another depends on the goal of the monitoring [16], [17]. Several studies have used leg-mounted sensors to monitor hens' activity and movement; however, this method is inappropriate for use in commercial settings owing to technical constraints and expensive prices. The behavior and health of hens might be monitored with the use of video evaluations based on optical flow. Video-based tracking is one example of automated tracking. When it comes to evaluating biometric characteristics like activity, mobility, and illness prediction, video-based monitoring outperforms animal wearable sensors. This is happening as a result of the measures' potential for easy expansion in practice. Also, hens experience less stress when they are not captured and handled.

Real-time evaluations employing video and image analysis, as well as self-monitoring and surveillance systems for animal behavior, are receiving more attention in order to keep up with the rise of the precision livestock farming industry. Monitoring systems can automatically measure phenotyping data, such as the core body temperature of chickens as detected by thermal imaging [18], their behavior as they move and interact with one another [19], their productivity as measured by their weight [20], and the number of eggs they lay [21]. Individual tracking, genome-wide association studies to improve breeding, keeping track of each animal's identity, tracking their activity and space use in real time, assessing group-level activity, being able to tell each animal apart, spotting abnormal patterns early, and spotting social and behavioral issues in chickens all require immediate automated monitoring, surveillance, and evaluations.

The major contribution of this paper has added on the below.

- This paper examines chicken behavior analysis using computer vision. To assess chicken health, computer algorithms monitor their movement, posture, and other behaviors.
- To use computer vision for the purpose of detecting chicken diseases and keeping tabs on their prevalence.
- To monitor the chicken's health using computer vision by doing a comprehensive literature review.

The rest of the paper is organised as follows: II. Motivation, III. Challenges, IV. Related Works, V. Methodology, VI. Selected papers for chicken detection and VII. Conclusion.

II. MOTIVATION

There are several key motivations for analysing chicken behavior using deep learning:

1. Improved animal welfare: Deep learning can help identify patterns of behavior that may indicate stress, fear, or discomfort in chickens. By understanding these behaviors, farmers can adjust conditions to improve the welfare of the chickens, leading to healthier, more productive animals.

2. Increased efficiency in farming operations: Understanding chicken behavior can also help farmers optimize their operations for maximum efficiency. For example, deep learning algorithms can help identify the best times to feed chickens, adjust temperature and lighting, or manage other environmental factors to improve the health and well-being of the chickens.

3. Better disease management: By analysing behavior patterns, deep learning can also help detect early signs of disease, enabling farmers to intervene and prevent the spread of illness before it becomes a widespread problem.

4. Increased food safety: Understanding chicken behavior can also help improve food safety by enabling farmers to identify and isolate any chickens that can be carrying or spreading disease.

Overall, the use of deep learning for analysing chicken behavior offers a powerful tool for improving the efficiency and welfare of farming operations, and ensuring the safety and quality of the food we consume.

III. CHALLENGES

Many procedures used in livestock production, from the beginning of an animal's existence until the instant before it is killed, have been proved to be traumatic and distressing to the animals involved. The profit margins of farmers are diminished as flock numbers increase. In order to promote disease detection and chicken welfare, it will be necessary to create disease prevention strategies.

In chicken-related machine vision research, behavioral detection algorithms based on brightness patterns in two-dimensional videos have been created [21]. There is still a need for models and methods that can identify and keep tabs on large flocks of chickens.

Continuously assessing animals on an individual and or group level eliminates visual assessment losses due to occlusions and related losses. Customized and per-herd assessments of cattle are now achievable and precise thanks to the adoption of AI-assisted technologies, which were previously useless and wrong on large-scale commercial farms [4].

Farmers need self-driving machinery to collect data on their animals, which might be used to assess the health of the herd. When it comes to providing the best possible care for their livestock, farmers really use some assistance and could significantly benefit from automating. Animal needs are easily identified by farmers if they maintain a close check on their livestock. Visual camera analysis alone may provide daily insights by evaluating injuries, lameness, feeding events, and the animals' activities, social interactions, and emotions. Due to the system's reliability, continuous monitoring of the animals is possible we can keep an eye on the animals round-the-clock. Farmers gain from this monitoring in a number of ways, including better animal health and welfare and a more competitive agricultural sector.

IV. RELATED WORKS

There has been a recent increase in research applying deep learning technology to applications like illness diagnosis and the categorization of chicken species behavior. Please see Table 1. No studies using the You Only Look Once model or under occlusion circumstances to identify, count, or track chickens have been published as of yet (Yolo V5). A preliminary set of shape and contour detection algorithms is used to begin the tracking phase. For each of these initial detection, a unique identifier is produced based on the image coordinates (video frames), and the tracking technique continues as the chickens traverse the video frames. Occlusion, background clutter, and differences in appearance make it difficult to notice and monitor chicken movement. When a chicken is obscured by another item, such as a feeder or another chicken, it is said to be occluded. There is a greater likelihood that the chicken may disappear and then resurface between video frames. Chicken feathers may have a similar color to the feeders, water nip dispensers, and other things on the chicken-rearing floor, making it more difficult to observe progress. In the absence of context, several viewpoints of a chicken may result in recordings of the chickens sounding significantly different. This can prevent the chicken from being identified.

TABLE 1. Investigations into chicken (poultry) identification using deep and machine learning.

Model	Developed Applications	Dataset	Location of data collecting	Results	Authors
The sound of a chicken CNN (There is no video or picture data.)	Detection of avian influenza	5 chickens' audio files	Biosafety laboratory under strict control	97.4%	[23]
CNN	Evaluation of animal behavior	3087 chickens, 12,000 photos.	The Rooster House	99.17%	[24]
Yolo	broiler chickens after being stunned	2319 images from 12 broiler chickens	Animal care facility	94.74%	[25]
Chicken behavior analysis using image processing	Behavior analysis	55 minutes videos from the chicken farm	In Paris	86.4%	[26]
Chan-Vese method and Transform Function (TF)	Weight measurements for the chicken	2440 images from 30 chicken	Ramin Agriculture and Natural Resources University	98%	[27]
Machine vision-based monitoring system for broiler chicken	Chicken detection analysis	34,280 images	Isolated controlled environment chambers	97.5% and 97.8%	[28]
Fully Convolutional Networks (FCN)	Density map estimation	100 images from few chickens	Chicken coop	16%	[29]

There is also a lack of literature on the topic of determining the activity trajectory and motion route of chickens, which includes identifying, detecting, counting, tracking, and measuring the chicken's movements. Although remarkable accuracy was shown in the small datasets used for the studies listed in Table 1, real-world performance outside of lab conditions would fall short of expectations. Also, several activities must be integrated by a single model to accomplish the complex task of collecting data based on hens' movements and then identifying individual chickens.

In this work, a Deep type Yolov5-based model was created to meet the requirement for real-time monitoring of the chicken's motion and activity [29]. Yolov5 is an Ultralytics application developed in 2020 [30] that improves detection accuracy and throughput in real time. The suitable method finds the activity of both individual chickens and groups of chickens in real time. You can keep track of where the chickens' coop is, how fast they walk, how far they go, when they eat based on their activities, and how they act in other ways [29].

As it is difficult, demanding, and time-consuming to identify and monitor visually identical, unmarked chicks in big flocks, there is an urgent need for automated measurement systems for agricultural animals, especially poultry. This study built an algorithm based on machine learning to instantly translate vast volumes of unstructured data from automated video recording devices into phenotypic evaluations of chickens. Although identifying, numbering, and monitoring the chicken are the primary goals of this research, classification is unnecessary.

The rising popularity of poultry is attributable to the low cholesterol, low fat, and high protein composition of these meats [31]. Yet, environmental factors, disease outbreaks, the breeding process, and proactive management are all essential for optimal chicken production. So, in order to reduce the prevalence of contagious diseases, boost productivity, and keep broilers in good condition, it is essential to use appropriate health and welfare management practices. Yet, the conventional methods of chicken and poultry welfare management are plagued by the inefficient use of resources such as labor and money. To this end, the combination of IoT and ML has been seen as a potentially game-changing tool for delivering solutions like "smart poultry farming," "continuous data monitoring," and "prescriptive analytics" to help with issues like "efficient resource management" [32], [33]. Hence, [34] suggested the artificial intelligent enabled internet of things devices might assist chicken company operators increase output while dramatically cutting expenses.

Machine learning (ML) is a method of employing computers to discover new facts and insights using analytic and a learning process [35]. There are several instances in the literature of how Internet of things technology has been used to monitor and control environmental conditions in chicken coops [31], [36]. The Internet of Things can be integrated into chicken leading to greater productivity, security, and financial gain [33]. Input of IoT data into ML has been used to categorize illnesses such as zoonotic poultry infections, which have disastrous consequences for poultry productivity and human health [22].

The system described in the research recognises chickens behaviour in a poultry farm using a Kinect sensor and convolutional neural networks (CNNs). It is a major improvement in the identification of domestic animal behaviour using deep learning, outperforming previous techniques with an amazing 99.17% accuracy in identifying flock behaviour images [23]. The article discusses the difficulty of spotting stunned grill birds in commercial settings. The paper presents an enhanced YOLO + MRM algorithm that distinguishes between three shocked states—insufficient, suitable, and excessive—with an amazing 96.77% accuracy. The algorithm's processing speed enables it to process more than 180,000 broilers every hour, outpacing conventional techniques and requiring little experience in picture identification. This study sets the framework for automating the electric stunning method used in the poultry industry's vital step of detecting stunned grill chickens [24].

This article analysis the latest AI-enabled IoT solutions for poultry welfare management and their impact on chicken health and welfare [37], [38], [39]. Researchers have looked at ML's usage in broiler growth and health prediction [40], while others have studied analytical advances in animal health and welfare monitoring [41]. Nonetheless, a comprehensive review of the most current studies using AI-enabled IoT utilizing ML is still a desired but understudied problem.

This research was to synthesize existing literature and provide a coherent overview of the present state of and potential future developments in welfare management in chicken production enabled by digital technology. The goal of this research was to give technical guidance for developing more effective digital solutions for monitoring the chicken production by focusing on the most current research advancements in this area. The authors discussed not only the fundamental elements of the model, but also how data is measured and what types of data are measured. They also discussed the gear and software used to control the health and well-being of chickens, as well as the processes involved in doing so. This research therefore satisfies the requirements of poultry managers and others concerned with the effective administration of animal welfare using IoT systems enabled by artificial intelligence.

V. METHODOLOGY

In order to conduct a comprehensive literature search, we followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. The PRISMA [42] instructions show you how to assemble a wide range of sources to serve as the basis for your evaluation. Figure 1 depicts the PRISMA steps, together with the number of articles retrieved and kept at each stage, for this review.

A. STANDARDS FOR ELIGIBILITY

The literature was reviewed regardless of when it was first published. There was an exclusive focus on English-language, peer-reviewed literature. Animal-based (body-worn) sensor research and studies focusing on non-behavioral factors, such as body weight, were also disqualified. The only recognized research used conventional or 3D cameras to monitor the behavior of cattle and poultry automatically (machine vision).

B. SOURCES OF PAPER

Among of the databases queried were Google Scholar, Web of Science, PubMed, and the ACM Digital Library. To uncover new sources of knowledge, we also used Google to search the grey (non-commercially published) literature. In March 2020, literature from these databases was gathered.

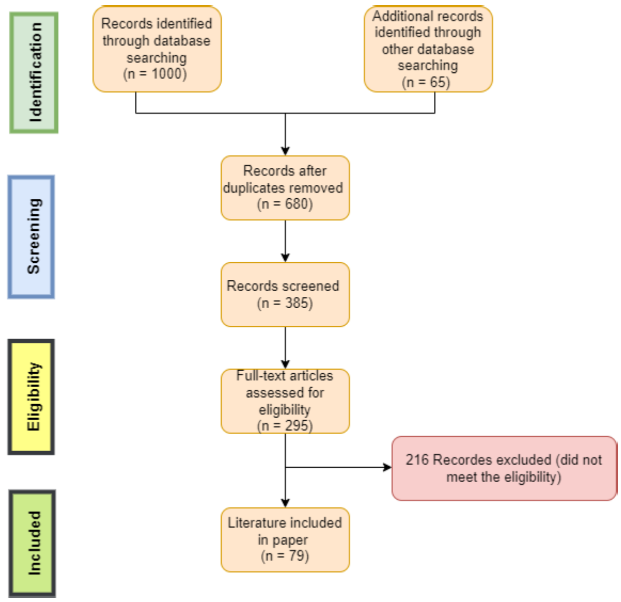

FIGURE 1. The systematic review followed by PRISMA process for article selection.

C. PUBLICATION SELECTION PROCESS

There was a comprehensive search of all databases using the following key phrases: automatic behavior management system; automatic livestock behavior management system Chicken behavior + automatic; Expenditures on things like behavior + videos + livestock; automatic + automatic behavior detection + chicken + video-based behavioral analysis + chicken + chicken + behavior + video detection. To ensure that all possible variations of the search query were accounted for, an asterisk (*) was utilized.

VI. SELECTED PAPERS ON CHICKEN BEHAVIOR AND HEALTH MONITORING

In [43] this article provides a comprehensive analysis of studies that have looked at the use of artificial intelligence (AI) in IoT applications for managing the health and well-being of chickens and other poultry. This study focuses on the well-being of chickens because of the difficulties of modern poultry management, this is why they have to deal with strict monitoring systems and defined standards for animal welfare evaluation, especially with regards to ensuring the health of broilers and preventing disease outbreaks.

In [27] this research provides a machine vision-based monitoring system for tracking the movement of broiler chicks via an experimental setup. Two sets of broilers, one serving as a control and the other as a treatment, were housed in completely separate rooms and monitored in parallel. A depth camera and a video camera were used to monitor the hens in order to classify data and develop a predictive model of the chickens' health, respectively.

In [44] this study presents a novel method for autonomously assessing feed intake in broiler chicks via the use of sound technology. An algorithm was developed

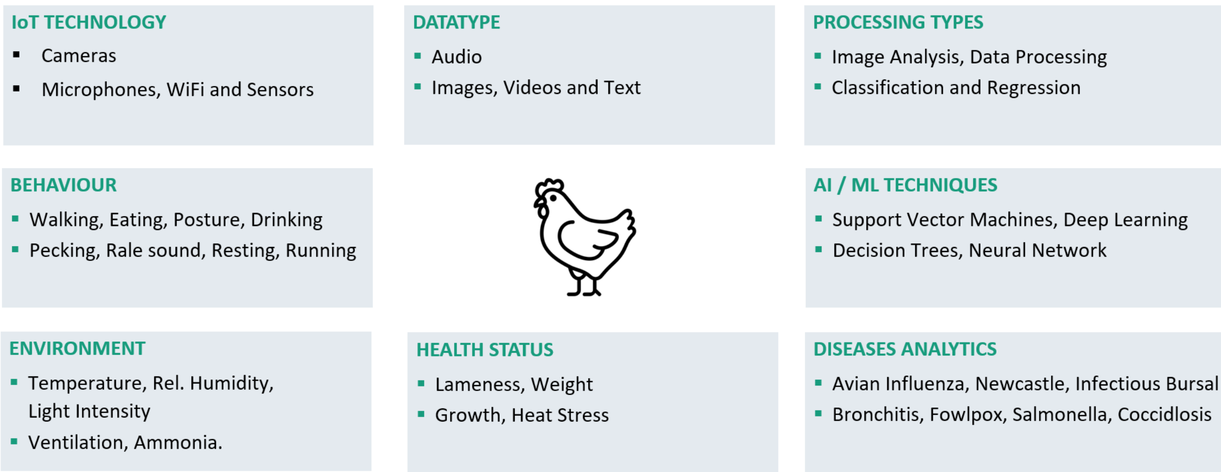

FIGURE 2. Overview of the digital technologies for chicken health and welfare.

TABLE 2. Using IoT, deep learning, and machine learning to observe poultry behaviour and surrounding conditions.

Models	Evaluates	Purpose	IoT Devices	Authors
Convolutional Neural Networks and Long Short-Term Memory	Image from a chicken	Recognizing mediocrity	Cameras	[61]
Convolutional Neural Networks, Long Short-Term Memory and Gated Recurrent Unit	Sound	Sex differentiation	Digital voice recorder, Camera	[57]
Convolutional Neural Networks	chicken behavior detection are eating, drinking, and jumping	Calculate a rough chicken population density	Cameras	[62]
Deep Neural Networks	Events	Behavior categorization, pose estimate	Cameras	[33]
Recurrent neural network	Trampling, flapping chickens	Eat and talk normally.	Microphones	[63]
Convolutional Neural Networks	Laying hen voices	Learn to identify the sounds of laying chickens	Microphones	[64]
Deep Neural Networks	Movement speed	Target tracking	Cameras	[65]
Lasso	Age, temperature	Heat stress	Thermal sensors	[66]
Generalized Sequential Pattern algorithm	Consuming food, walking about, rummaging through trash, and taking dust baths	Temperature strain	Cameras, Sensors	[67]
Artificial neural network	behaviours	Distribution of chickens on the floor analysis	Cameras	[68]

in this research to classify the varied pecking sounds of broiler chickens. Afterwards, researchers looked at how clucking sounds related to total food intake. The algorithm's results were put up against estimates of feed consumption based on weight measurements and visual inspections.

In [45] research, the authors report the development of a fully automated system for tracking food consumption and body mass index in real time. Electronic scales, RFID readers, and data transmission modules were all included into the system so that it could keep track of both the animals' food intake and their overall body mass. Multithreaded software architecture development for a client-server-based distributed system.

Due [46] to the natural decline in broiler activity in commercial homes, we discovered in this research that the accuracy of broiler activity declined with longer sampling intervals, with the 0.04-s interval giving the most locations affected. The research provides useful information on how to sample images to accurately estimate the broiler activity index, which might be used to address growing public concern about the well-being of chickens.

In [47] order to automatically determine the temperature of the broiler's head, a special algorithm was devised. The broiler's head size was determined with the use of adaptive K-means clustering and elliptical fitting. The surface temperature of the head was determined by measuring the atmosphere in the head-space. Results from testing the

TABLE 3. IoT, deep, and machine learning for chicken healthcare analysis.

Models	Evaluates	Purpose	IoT Devices	Authors
Convolutional Neural Networks	Fecal images and fecal samples	Early diagnosis of the poultry diseases	Cameras	[73]
BiLSTM	Sound and images	Diagnose respiratory issues	Camera	[74]
Convolutional Neural Networks, Recurrent Neural Network	clinical symptoms, disease warning, automatic monitoring	Process of early warning decision-making	Cameras, Temperature sensors	[75]
Support vector machine	Sound	Diagnose respiratory problems	Acoustic box	[76]
RE	Faeces/soil sample, temperature, RH, wind speed	Salmonella prevalence	Cameras, sensors	[77]
Deep neural network	Date, current weight, desired weight, and food consumed	Identify non-laying chickenss	RFID/Historical	[78]
Convolutional Neural Networks	Chicken images, feather texture, postures	Diagnose respiratory problems	Cameras	[79]
Support vector machine	Postures	Diagnose respiratory problems	Cameras	[80]
k-nearest neighbors algorithm	Imagine and hear a chicken	Diagnose respiratory issues	Cameras, Sensors	[81]
Radio-frequency	Things to take into account include the region, the subtype of the virus, the breed of broiler, and the population density	Historical data	Diagnose respiratory problems	[82]

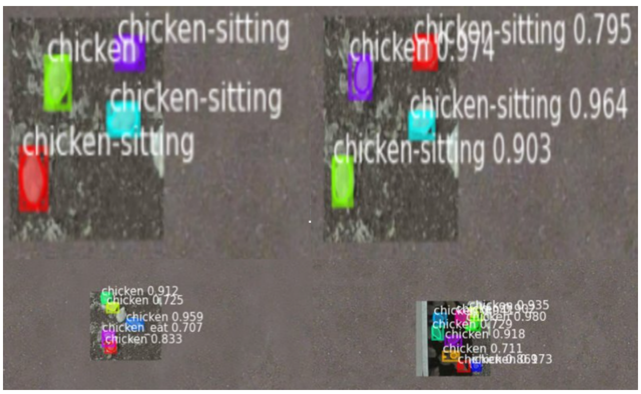

FIGURE 3. Chicken behavior monitoring system.

method in MATLAB® (R2016a) showed that 92.77 % of broiler thermal images included enough information to accurately identify the head area.

In [48] this work is an attempt to acquaint animal behaviorists unfamiliar with machine learning (ML) to the potential of these approaches for assessing intricate behavioral data. The notion of ML is first introduced, and then many examples of research on animal behavior in which ML has proven useful are discussed. Several types of learning, both unsupervised and supervised, are presented once the ML framework has been introduced.

The [49] goals of this study were to 1) define the dynamic declines in body surface temperature after euthanasia, and 2) evaluate the accuracy of automatically detecting dead broilers at two stocking densities using thermal and visual photographs. The tests were conducted in a commercial broiler house on a weekly basis over the course of two 9-week production cycles. Inside this 0.80 m 0.60 m area, we housed experimental broilers. Above the fenced area, a dual-purpose camera recorded thermal and visual data from the broilers for 20 minutes at each stocking density. In order to distinguish between alive and dead broilers in thermal images, an algorithm was developed. The algorithm found the dead broilers and pinpointed their positions by comparing the processed thermal and visual images collected at the same time.

In [50] the purpose of this paper is to develop a technique to employ a binocular vision system to autonomously follow the behavior of caged chickens. Using an improved active contour model for 2-D image segmentation, image separation was improved. Second, binocular cameras collected pairs of rectified images to reconstruct the 3D vision.

In [51] this findings, a computer vision system is proposed that can monitor pigs in group pens for signs of idleness and raise an alarm if it sees any. The proposed image processing and logic analysis approach called ''DepInact,'' the system was able to track the amount of time that individual pigs kept in groups were idle. The new technique was tested by gathering 656 depth data and color images four days apart.

In [26] the use of a dynamic model and digital image processing, this research set out to ascertain whether it was feasible to provide an approximation of the body weight of broilers. In this experiment, 30 chickens were shown 2440 times from above. A generalized Hough transform and an elliptical fitting method might be used to pinpoint the location of the hens inside the enclosure. Using the computer vision method, the heads and tails of chickens were successfully detached. Afterwards, six different measurements of the body were determined by computer.

In [52] this paper the author has created a method for tracking sneezes from chickens in the presence of background noise and mobile fowl. 51 hens were used in the investigation, and their sneezes were recorded. Seven hundred sixty-three sneezes were transcribed from 480 minutes of audio recordings. The number of sneezes with accurate labels was first evaluated. Thereafter, spectral subtraction filtering was used to segment the raw audio stream into short, high-energy segments that might stand in for sneezes.

A. POULTRY WELFARE MONITORING USING IOT AND MACHINE LEARNING

The findings from the semantic literature review (SLR) that directly address the concerns posed above are presented below. Tables 2 and 3 show the results obtained. Specifically, the study indicated that IoT and ML were most helpful in controlling poultry health and welfare when utilized for the following two purposes: (1) monitoring behavior and environment, and (2) disease analysis. Figure 2 is a comprehensive summary of how digital technologies are being used to improve the health and well-being of chickens. Tools, data, processing kinds, illnesses, and health condition are all covered, along with a description of artificial intelligence and machine learning methods and approaches.

B. BEHAVIOR MONITORING

Methods in Table 2 that track the feeding, sleeping, and running habits of chickens from afar are highlighted (temperature, relative humidity). This intervention is the main objective is to help chicken farmers by automating data collection using Internet of Things (IoT) technologies. Without endangering nearby people or animals, these systems continually monitor broilers.

With the purpose of assisting farmers with welfare issues, especially risk assessment, these research concentrate on the physiological reactions of broilers, such as their respiration rate and cloacal temperature [53], as well as posture and activity, for further in-depth analyses of behavioral expression [54]; [55]. A similar experiment was carried out by [56], in which the researchers watched over and adjusted the environment in which the hens were housed. In addition to this, [57] maintained a close check on the automated broiler house in order to report any issues that arose with the feeders or the Waters. The figure 3 shows the chicken behaviour monitoring system, where we detected the chicken with possible classifications.

1) PREDICTING DISEASE

The chicken business has a major challenge in terms of diagnosing illnesses at an early enough stage to prevent illness from spreading and thereby avoid the spread of disease. The time and energy needed to maintain large animal populations, as a result of various studies, it seems that this threat can be mitigated thanks to improvements in technology that enable the accurate, quick detection and diagnosis of poultry illnesses. Ten articles were selected for this section (Table 3), accounting for a percentage point of the total number of papers assessed. The articles in this collection analyze successful strategies for preventing poultry diseases. Research by [65], for instance, sought to lessen the burden of manual observation and human judgment. Influenza a in chickens and the Newcastle disease virus [66], [67]. Standard methods for detecting sick hens include looking at their eating habits [68], their posture and mobility [32], and their sounds [52].

VII. CONCLUSION

This article reviews the potential uses for artificial intelligence (AI) and the Internet of Things (IoT) in the poultry sector, namely for the monitoring of chicken health. Many poultry welfare system case studies showed how AI-enabled Internet of Things processes data, hardware, and software. In order to prevent disease outbreaks, this research revealed poultry IoT and AI therapies and created the foundation for improved chicken welfare. This study makes a contribution to the current body of knowledge by offering direction to stakeholders on how to better understand and apply cutting-edge digital technologies. By using a knowledge of technology for the purpose of monitoring the welfare of chickens and improving the production process, it is possible to make poultry production more efficient, quick, and cost-effective. As this is the case, the research will lead to the creation of brand-new ideas in technology with the potential to raise the productivity and financial success of the poultry industry.

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