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The Impact of Artificial Intelligence Techniques on The Growth and Carcass Performance of Broiler Chickens, A Review

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Abstract:
The efficiency and productivity in many areas such as animal science could increasingly be improved by artificial intelligence (AI). Because generating and analyzing large amounts of data in real time is now feasible, the use of smart technologies in modern farming systems is gaining ground, which further strengthens AI's role in livestock production. Machine learning (ML) is one of the main types of AI that enables a computer to learn through a dataset and predict a test outcome without being explicitly programmed to do so. Predicting outcomes based on an input data is statistically, the outcome of a machine learning algorithm.
Machine learning methods show better prediction performance in broiler production. Studies have shown that broiler growth and body weight can be predicted with 98% to 99%. In addition, neural network models detected the presence or absence of ascites in broiler chickens with 100% effectiveness. When machine-vision techniques were incorporated into SVM models, accuracy reached 99.5% for identifying healthy and avian influenza infected chickens in the SVM literature (Arowolo, 2017). It may be concluded that ML is likely to play an essential role in broiler growth prediction and health disorders detection.
As a result, the study seeks to examine broiler growth and health predictions through machine-learning techniques. Due to its ability to deal effectively with large datasets and model nonlinear relationships appropriately, ML has great potential to complement or replace conventional approaches in poultry-production systems of the future.

Keywords- Artificial intelligence, production efficiency, machine learning, broiler chicken, body weight.

Introduction

In recent years, the global poultry industry has experienced significant transformation due to rapid technological advancement, particularly the development and adoption of artificial intelligence (AI) technologies in various stages of animal production. The poultry sector has been especially responsive to these technological innovations because of its high sensitivity to environmental and health-related factors, as well as the continuous need to enhance production efficiency, minimize costs, and improve the quality of final products. Artificial intelligence is a field within computer science that focuses on developing systems capable of simulating human reasoning and making data-driven decisions [1]. The application of AI technologies in poultry farming has facilitated the development of advanced approaches for monitoring bird growth, assessing health conditions, managing nutrition, and regulating the internal environment of poultry houses with a high level of accuracy [2].

There is an increasing demand to expand the use of artificial intelligence in animal science in order to enhance production efficiency through smart technologies at the farm level. These systems generate large volumes of data, which can be analyzed in real time and used to strengthen AI capabilities through machine-learning algorithms. Machine learning (ML) represents an important branch of artificial intelligence that allows computer systems to learn from data and generate predictions without the need for explicit programming. Using machine-learning approaches, the prediction accuracy of broiler growth and body weight has been reported to reach between 98% and 99%. Furthermore, when support vector machine (SVM) models are integrated with machine-vision techniques, an accuracy of approximately 99.5% can be achieved in distinguishing healthy chickens from those infected with avian influenza. These findings demonstrate that machine-learning algorithms can effectively predict broiler growth and contribute to improved disease detection [3].

Through the use of intelligent systems, poultry-house environmental conditions can be automatically adjusted, and early warning alerts may be generated when potential disease symptoms are detected. Such capabilities help reduce mortality rates and enhance overall flock performance [4]. One of the most significant outcomes of implementing artificial intelligence in poultry production is the improvement of growth performance and the reduction of the rearing period. Smart systems can optimize feeding strategies and ensure more accurate feed distribution, which leads to improved feed conversion efficiency and increased final body weight. In addition, imaging and visual analysis technologies can enhance carcass evaluation by improving classification accuracy and enabling precise estimation of meat and fat proportions, thereby contributing to better carcass quality [5].

The benefits of applying artificial intelligence in poultry production extend beyond technical improvements. AI-based solutions also provide important economic advantages, as farmers can reduce resource waste, increase productivity, and achieve greater profitability [6]. Considering the ongoing challenges facing the livestock sector, Accordingly, the integration of artificial intelligence technologies into animal production systems is no longer merely an option but has become a fundamental requirement for achieving long-term sustainability and enhancing biosecurity [7]. Therefore, the present study aims to evaluate the effects of artificial intelligence technologies on broiler growth performance, feed conversion efficiency, and carcass quality. This objective will be accomplished through a comparison between a conventional production system and an AI-supported production system, followed by a scientific analysis of the outcomes resulting from this technological transformation

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Materials and Methods

We identified search terms related to precision livestock farming and poultry production and searched multiple databases. Reading analysis included with precision techniques, PLF techniques, environmental conditions, sensors, RFID, machine learning, audio analysis, optical flow analysis, broiler growth, broiler welfare, image analysis, Thermal imaging, feed intake monitoring, and production-related constraints. The largest number of relevant studies was generated by combining these keywords in different ways.

Precision tools for controlling environmental factors.

Standards for the environment are an important factor in animal welfare, bird health and efficient poultry production.

Heat stress is one of the most prevalent environmental constraints in broiler chickens (meat type birds) due to their high metabolic rate and rapid growth. [8] When the temperatures of a certain environment exceed the thermoneutral zone of the birds, the dissipation of heat becomes difficult, which may cause health problems and lower productivity may also lead to food safety issues [9].

Poultry houses are not evenly heated and so birds tend to congregate in areas that are cooler in order to regulate body temperature. Nonetheless, heat stress can compromise the immune system and also cause digestive disorders [9]. Moreover, heat stress may reduce growth performance and lower productivity [10]. The ventilation, heating and cooling system of every broiler house should be designed and equipped to control temperature, carbon dioxide concentration, ammonia level and relative humidity [11]. Good ventilation is especially essential to regulating the internal climate of livestock buildings while maintaining good environmental conditions in the different sections of the poultry house [12].

When temperatures and humidity levels get hot, bacterial growth and the degradation of organic matter increases. The latter often forms ammonia (NH3). Also, the gases like carbon monoxide (CO), carbon dioxide (CO2), methane (CH4), and hydrogen sulfide (H2S) may build up in poultry houses. When concentrations are high enough, these gases can be toxic and damage the health of birds, potentially causing disease or death in poultry flocks [13].

Nowadays, modern poultry management systems make use of technology to overcome these environmental problems The combination of artificial intelligence (AI), the Internet of Things (IoT), and edge computing is enabling the design of intelligent automated systems that can monitor, predict and control environments in real-time [14]. In this regard, the present work deals with monitoring and predicting environmental conditions of poultry houses through an intelligent system Poultry-Edge-AI-IoT. The system takes the readings from the wireless sensor network. In addition, this information will undergo several stages. For instance data segmentation, data storing, data preprocessing, filtering, extracting and transmitting.

The Poultry-edge-AI-IoT framework uses an Internet of Things (IoT) along with Artificial Intelligence (AI) and edge technology to intercede potential occurrence of stressors, harmful gas concentrations and changes in environment inside poultry houses. The system has been designed to be modular and scalable. The experimental findings showed that the Poultry-Edge-AI-IoT platform could reliably monitor poultry house environments and measure harmful gases such as CH4, H2S, NH3, CO and CO2, dust concentrations and ammonia emissions from the poultry house. The ability to monitor these items is vital for environmental conditions and animal health in poultry production systems [15]

Accurate tools for assessing bird behavior, welfare, and health

Audio Analysis

Many animals use sounds to indicate their internal or external conditions. For example, mating calls, social contacts, and stress signals. Chickens can make about 30 different sounds [16], which may signal they are ready to mate, feeling pain or stress, or want something [17]. Variations in vocalizations often indicate physiological and behavioural states [18]. Most vocal signals emit refined information regarding the motivation and internal state of the bird[19].

The food-calling behavior of maternal hens is driven by both external environmental cues (food value) and audience factors (chicks' presence/behavior). These findings align with and support previous research documented in male chickens [20]. The food-calling behavior of maternal hens is modulated by both resource value and social environment. These findings closely parallel and support previous research observed in male chickens. Chickens call with varying frequencies and rates when they feed on different types of food [23]. The vocal communication of an individual thus carries important biological information that is encoded in acoustic characteristics such as sound amplitude, frequency, duration, call rate, and energy distribution [24].

Technological advancements have now been used increasingly for vocalization analysis in poultry monitoring. The use of AI and bioacoustic techniques will present a novel methodology for automated sound analysis to non-invasively monitor poultry welfare. Recent systematic research shows a gradual shift from conventional vocal feature extraction methods (such as Mel-Frequency Cepstral Coefficients (MFCCs) spectral entropy, and spectrogram analysis) to deep learning approaches. Convolutional neural networks, long short-term memory networks, and attention-based architectures can be included among the models Furthermore, models based on self-supervised learning such as wav2vec2 and Whisper have improved the ability to analyse acoustic signals.

Recent studies have confirmed that several edge technologies can be used to deploy TinyML frameworks in poultry production systems for real-time response. These systems reduce acoustic messy and computation difficulty in commercial poultry houses. The potential of advanced applications for real-time welfare assessment is promising as these applications include emotion recognition, disease detection, and behaviour monitoring. As a result, AI-powered vocalization analysis is transforming our understanding of the communication and welfare assessment of poultry production systems [25].

It is believed that animal welfare could be assessed in livestock and poultry through acoustic monitoring. Bird sounds are biological signals which reveal the health status, behavioural and stress condition. Using LSTM networks for temporal modeling indicated that vocalizations under visual and auditory stress differ. This may serve to identify habituation as well as stress-based vocalizations. The performance of the model was validated using stratified cross-validation and several statistics like the F1 score and Matthews correlation coefficient showing strong classification performance and generalisation capabilities

This alternative analytical approach emphasizes model interpretability, thereby enhancing the understanding of physiological and behavioral processes in poultry [26]. Using this methodology, a vocalization analysis system was developed to identify and classify four categories of broiler chicken sounds, including contentment vocalizations, distress calls, short whistles, and warbles. The system was also designed to filter background noise and other environmental sounds in poultry houses [27].

Image and video analysis

The quick development of broiler chickens often results in restrictions on movement and reduced physical activity levels [28]. When activity decreases, it can indicate the presence of leg and foot disorders resulting from rapid growth and poor litter quality, such as knee burns and plantar fasciitis. Broiler production system usually faces such conditions [29, 30]. Lesions of this type cause pain and make movement difficult. This can reduce feed and water intake and lead to weight loss [31].

The poultry industry today is however faced to multiple problems such as disease outbreaks, shortage of manpower, lack of monitoring, and rising public concern for animal welfare. These issues have been resolved with growing deployment of deep learning-based monitoring systems. The automated poultry monitoring and management in the study used the YOLOv11 algorithm.

We collected a dataset having 330 chicken images from the farms in Thailand under different environments. By rotating, adjusting brightness and saturation, we generated several images to expand the dataset to 1716 images. Trained with NVIDIA Jetson Orin Nano development kit, YOLOv11 was evaluated based on precision, recall and mean average precision (mAP).

The precision, recall and mAP values of the model are 0.964, 0.938 and 0.963. The system operated optimally in both optical and thermal modes under various lighting and environmental conditions. The proposed methodology has exhibited a capability of real-time monitoring and tracking of multiple chickens. Farmers can prevent disease, improve feed efficiency, and better manage their farms.

This study proposes a fully automated, scalable, and accurate poultry monitoring system that contributes towards the development of smart agriculture. Poultry production systems in modern times can certainly benefit from the use of such systems as they can improve sustainability, enhance efficiency and ensure better animal welfare [32].

Tools for estimating precise nutrition and growth of broiler chickens

Monitoring water and feed consumption

The production costs of poultry are incurred up to approximately 70% to 80% and 80% feed must be controlled accurately [33]. Conveyed by determining what weight of feed gets given to the birds and feeding it as per the age and growth need of the birds. Feeding schedules and frequencies can be altered, particularly in broiler breeder birds. In addition, feed consumption and feed conversion ratio could be computed to aid the production management [34]. Flocking costs may decline, and body weight may increase with precision feeding [35].

An electronic load-cell type scale and a flow meter, a water pipe flow measuring instrument, are fitted on the water pipe and feed trough of broiler houses to measure feed and water intake. In each row of the poultry house or throughout, these devices are utilized to measure feed and water intake. These tools may also enable the identification of health issues in birds and technical failures related to feed quality or feeding systems [36, 37].

According to a number of studies, radio frequency identification (RFID) systems can serve as cutting-edge sensors for the tracking of individual feeding and drinking behaviour of poultry and pigs in experimental conditions [31, 32, 33, 34, 35, 36]. In the case of broiler chickens, the reported accuracy is 92.5% to 99% (38). Using a Bayesian regression model to analyze optical flow could also be used to estimate birds' feed and water intake [39]. To monitor the monitor feed-line operation medical problems computer vision could be used to find broiler distribution index [40]. The access of feeder was limited and it noticed lower distribution index. The accuracy of this method as reported is 95.24%. The literature reveals no major inconsistency that can prove the technology infeasible [41].

In birds, metabolic robots can effectively enhance feed conversion ratio by 4% by regulating feed-dose in accordance with the demand of birds at different age or growth stages and control of feeding time [42]. Economically efficient broiler production is essential for livestock production and being practised in many countries. Weight data collection can provide useful information regarding growth rate, body weight, FCR and health status of the bird [43]. Feyiyan et al. (44) state that individual monitoring of broiler growth can be accomplished using radio frequency identification (RFID) technology, coupled with electronic weighing. Nonetheless, researchers found a significant drawback of this system to be the attachment of the tags to the body of the bird, which may cause stress and lead to the values being unreliable [45].

The growth models are used in practice to estimate the chicken growth rate and nutritional requirement taking into account the feed composition and environmental conditions [46]. Variable growth equations can also be calculated [47] and further feed additives and economic enhancers may be added to the model to enable cost-effective feed formulation [48] A new precision feeding system for broiler farmers has been created in Canada. In this system, a feed station distributes feed portion-wise as per the difference between targeted body weight and actual body weight of the birds [49].

The use of artificial intelligence can give great benefits in several key areas of livestock production, including monitoring, prediction, and improvement of farm-animal growth as well as the management of pests, diseases, and biosecurity threats. Using AI to collect and analyze data from livestock farms can allow for more accurate predictions of consumer behavior, buying patterns, and market trends. Consequently, farms are increasingly relying on automated systems capable of lowering costs and improving the quality of products such as eggs, milk and meat [50].

Limitations of PLF techniques

The anticipated limitations and operational challenges of precision livestock farming (PLF) technologies should be investigated before implementation. Regardless of their usefulness to aid in planning, decision making and problem solving, these systems are both beneficial and disadvantageous which should be assessed accordingly [51]. While operational power outages, equipment breakdown, and data discard are likely to occur technical [52]. Problems like these can cause major headaches for farms that are reliant on PLF tools, which cannot always be sorted without expert backing [53].

Furthermore, devices or tags attached to the bodies of birds may affect their natural behavior and induce physiological and behavioral disturbances associated with stress. Examples include location-tracking systems used in broiler chickens, surface body-temperature monitoring devices, and implantable radio telemetry systems employed to estimate heart rate and core body temperature in laying hens. The use of such technologies may have adverse effects on bird comfort and welfare [54,55]

Future directions to overcome constraints

Since PLF technologies deliver real-time data regarding environmental conditions, animal physiology, health, welfare and production and location, they can help better support lean management and sustainability and resilience and improve decision-making for farmers.

Due to this, the role of PLF is predicted to become more important in present agriculture and economy[60] .Climate change adversely impacts the health and productivity of animals [57, 61]. As a result, it will still be a big challenge in the future to cut down it and prevent it from happening. This can be supported by precision tools which allow strategies reducing heat stress. For instance, continuously monitoring of the physiological parameters of animals and optimizing of feed intake to reduce metabolic heat production can allay the harmful effects of thermal stress. Precision nutrition can enhance animal health and feed efficiency and improve growth regularity and meat quality [10].
Stress and health disorders can be continuously monitored, early detected and promptly treated, which can reduce the suffering of the animals, treatment costs and production losses [58]. Precision technologies can also be connected to business-management software platforms. In addition, they can take on other functioning processes. This includes finance, regulation, and stock [59]. The PLF system is anticipated to evolve further along with mobile technologies, artificial intelligence and the Internet of Things and, thus, promising use.

Conclusions

The application of precision technology in agriculture and the poultry sector dates back to the 1980s, when the first forms of digital image processing emerged. With the rapid growth of information and computer technology, the range and type of PLF tools are expanding. Our review presented the available information sources on a wide range of PLF technologies applied in poultry production. Sensors provide continuous and real-time data on environmental conditions (such as temperature, humidity, ventilation speed, carbon dioxide and ammonia concentrations, etc. that are transmitted to the system. The extracted data can be used for control, and the farmer is concerned about any problems that might interfere with the process. 3D vision monitoring and digital image processing technologies, using deep learning algorithms, can detect bird welfare and disease with high accuracy (from 84% to 100%). Multi-purpose robots can also measure multiple parameters in parallel, saving energy and economy and helping to obtain a more accurate view of production and welfare.

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تأثير تقنيات الذكاء الاصطناعي على نمو دجاج التسمين وأداء الذبائح

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الخلاصة

يمكن تحسين الكفاءة والإنتاجية في العديد من المجالات، مثل علوم الثروة الحيوانية، بشكل متزايد بفضل الذكاء الاصطناعي .(AI) ونظرًا لأن إنتاج وتحليل كميات ضخمة من البيانات في الوقت الفعلي أصبح أمرًا ممكنًا الآن، فإن استخدام التقنيات الذكية في أنظمة الزراعة الحديثة يكتسب زخمًا، مما يعزز دور الذكاء الاصطناعي في إنتاج الثروة الحيوانية. ويُعد التعلم الآلي (ML) أحد الأنواع الرئيسية للذكاء الاصطناعي، حيث يمكّن الكمبيوتر من التعلم من خلال مجموعة بيانات والتنبؤ بنتيجة اختبار ما دون أن يتم برمجته صراحةً للقيام بذلك. ويُعد التنبؤ بالنتائج بناءً على البيانات المدخلة، من الناحية الإحصائية، نتيجة لخوارزمية التعلم الآلي. تُظهر أساليب التعلم الآلي أداءً تنبؤياً أفضل في إنتاج الدجاج اللاحم. وقد أظهرت الدراسات أنه يمكن التنبؤ بنمو الدجاج اللاحم ووزنه بنسبة تتراوح بين 98% و99%. بالإضافة إلى ذلك، تمكنت نماذج الشبكات العصبية من الكشف عن وجود أو عدم وجود الاستسقاء في الدجاج اللاحم بفعالية تبلغ 100%. وعندما تم دمج تقنيات الرؤية الآلية في نماذجSVM ، بلغت الدقة 99.5% في تحديد الدجاج السليم والمصاب بإنفلونزا الطيور وفقًا للدراسات المنشورة حول نماذج SVM (Arowolo, 2017) . يمكن الاستنتاج أن التعلم الآلي من المرجح أن يلعب دورًا أساسيًا في التنبؤ بنمو الدجاج اللاحم وكشف الاضطرابات الصحية. ونتيجة لذلك، تسعى هذه الدراسة إلى دراسة تنبؤات نمو الدجاج اللاحم وحالته الصحية من خلال تقنيات التعلم الآلي. ونظرًا لقدرته على التعامل بفعالية مع مجموعات البيانات الضخمة ونمذجة العلاقات غير الخطية بشكل ملائم،

فإن التعلم الآلي يتمتع بإمكانيات كبيرة لتكملة أو استبدال الأساليب التقليدية في أنظمة إنتاج الدواجن في المستقبل.

الكلمات المفتاحية: الذكاء الاصطناعي، كفاءة الإنتاج، التعلم الآلي، دجاج التسمين، وزن الجسم.