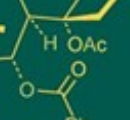
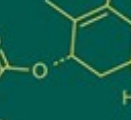
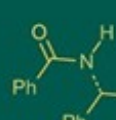


International Journal of Advanced Biochemistry Research



ISSN Print: 2617-4693
ISSN Online: 2617-4707
NAAS Rating (2026): 5.29
Indexing: Embase
IJABR 2026; 10(9): 623-631
www.biochemjournal.com
Received: 29-06-2026
Accepted: 23-08-2026
Published: 23-09-2026

Loukik Raut

Department of Animal Nutrition, College of Veterinary Science and Animal Husbandry, Kamdhenu University, Anand, Gujarat, 388001, India

Tanaya Ponshe

Department of Veterinary Pharmacology & Toxicology, College of Veterinary Science and Animal Husbandry, Kamdhenu University, Anand, Gujarat, 388001, India

Tathagat P Khobragade

Department of Animal Nutrition, College of Veterinary Science and Animal Husbandry, Kamdhenu University, Junagadh, Gujarat, 362001, India

Dileep Singh

Department of Livestock Production Management, College of Veterinary Science and Animal Husbandry, Kamdhenu University, Anand, Gujarat, 388001, India

Corresponding Author: Loukik Raut

Department of Animal Nutrition, College of Veterinary Science and Animal Husbandry, Kamdhenu University, Anand, Gujarat, 388001, India

Applications of artificial intelligence in poultry nutrition: A comprehensive review

Loukik Raut¹, Tanaya Ponshe², Tathagat P Khobragade³, Dileep Singh⁴

DOI: <https://www.doi.org/10.33545/26174693.2026.v10.i9h.10120>

ABSTRACT

Artificial intelligence (AI) is rapidly reshaping the way nutrients, ingredients and feeding programmes are managed across the poultry industry. AI in poultry nutrition combines machine learning, deep learning, computer vision, IoT and data analytics and converts farm and feed data into precise, data-driven feeding and management decisions. This review brings together recent peer reviewed evidence on the use of these methods across the poultry nutrition value chain, from the screening of feed ingredients for mycotoxin contamination, computer vision based monitoring of bird growth, feed conversion and health, neural network prediction of amino acid requirements, machine learning prediction of pelleted feed quality or pellet durability index (PDI), deep learning prediction of dietary metabolic energy and fully automated precision feeding stations that individualise nutrient delivery to individual bird. Representative quantitative outcomes are summarised, including classification accuracies exceeding 98 percent for deep convolutional networks used in faecal image-based disease screening, correlation coefficients above 0.9 between acoustic estimates of feed intake and reference weighing methods and a reduction in body weight coefficient of variation from about 14 percent to below 2 percent following deployment of a precision feeding station in broiler breeders. This review closes by identifying the principal constraints on wider uptake, namely capital cost, data quality for training of AI models, the shortage of technically trained personnel and concerns around data ownership and privacy. Future progress will require not only improving AI technologies but also developing affordable, reliable and user-friendly solutions that can work effectively under real farm conditions.

Keywords: Artificial intelligence, Poultry nutrition, Machine learning, Deep learning, Computer vision, Precision feeding

1. Introduction

In 1956, John McCarthy coined the term Artificial Intelligence (AI) and defined AI as “the science and engineering of making intelligent machines”. He also known as the ‘Father of Artificial Intelligence’. AI is the system's ability to correctly interpret external data, to learn from such data and to use those learnings to achieve specific goals and tasks through flexible adaptation. Nearly seventy years later, the descendants of that idea, machine learning, deep learning and computer vision, have moved out of computer science departments and into commercial poultry sheds, hatcheries and feed mills.

Modern broiler and layer operations already generate continuous streams of information on feed intake, water consumption, body weight, environmental conditions, mortality and increasingly, on individual bird identity through radio frequency identification and video surveillance. Traditional nutritional models, largely based on fixed nutrient requirement tables and regression equations derived from mean flock responses, were not designed to make full use of this volume and variety of information. Artificial intelligence offers a complementary approach: instead of assuming a single average bird, algorithms such as artificial neural networks, convolutional neural networks and long short-term memory networks can learn non-linear, individual level relationships between diet, environment and performance directly from historical and real time farm data (Sarker, 2021) [1].

The scope of AI application in poultry nutrition now extends across almost the entire feed to bird system. At the raw material stage, deep learning-based image analysis is being used to flag mycotoxin contaminated grain before it enters a feed mill (Leo, 2023) [2]. Within the mill, machine learning regression models predict the physical quality of the pelleted feed (Pellet Durability Index) that will be produced from a given formulation and processing set point (You *et al.*, 2022) [3], while deep learning models estimate the metabolic energy value of complete diets from ingredient composition (Wang *et al.*, 2023) [4]. On the farm, computer vision and acoustic sensing systems continuously track how much feed birds are eating, how quickly they are growing and whether their behaviour suggests early disease or stress (Aydin *et al.*, 2016; Okinda *et al.*, 2020) [5, 6]. At the individual bird level, precision feeding stations combine radio frequency identification,

load cell weighing and control algorithms to deliver a tailored ration to each bird several times a day, a level of nutritional precision that would be impossible to achieve manually (Zuidhof *et al.*, 2017) [7].

This review has three objectives. First, it summarises the conceptual foundations of artificial intelligence, machine learning and deep learning in language accessible to nutritionists and animal scientists who are not specialists in computer science. Second, specific AI applications relevant to poultry nutrition, organised along the feed to bird value chain and reports the quantitative performance of these systems wherever it has been documented. Third, it critically examines the practical limitations that currently restrict adoption of these tools, particularly in smallholder and developing country contexts.

2. Artificial intelligence, machine learning and deep learning: A conceptual framework

2.1 Definitions

John McCarthy defined AI as the science and engineering of making intelligent machines, while Kaplan *et al.* (2019) [8] describe it as a system's ability to correctly interpret external data, to learn from that data and to use what it has learned to achieve specific goals through flexible adaptation. Asif *et al.* (2024) [9] emphasise that AI systems perform tasks, such as reasoning, decision making and problem solving, that have historically required human intelligence. IBM defines AI as technology that enables computers and machines to simulate human learning, comprehension, problem-solving, decision-making, creativity and autonomy.

2.2 Categories of artificial intelligence

Artificial intelligence is conventionally divided into three broad categories according to the breadth of capability involved (Russell *et al.*, 2021; Goertzel, 2014; Bostrom, 2014) [11, 12, 10].

- **Artificial narrow intelligence (ANI).** Also called weak AI, this is the only form of AI in commercial use today. It is programmed or trained to perform one task, or a narrow family of related tasks, extremely well, but it cannot transfer that competence to unrelated problems.
- **Artificial general intelligence (AGI).** Sometimes called strong AI, this refers to a hypothetical system with human like breadth of reasoning, capable of learning and applying knowledge across many different domains without being separately trained for each one.
- **Artificial super intelligence (ASI).** A further hypothetical stage in which machine intelligence would exceed human intelligence across all relevant domains, including creativity and social reasoning. Discussion of ASI remains speculative and is included here only for conceptual completeness.

2.3 Machine learning

Machine learning is the subset of artificial intelligence most directly responsible for the applications described in this review. It allows a computer to identify patterns in data and to improve its performance on a task without being explicitly reprogrammed for every new situation (Alzubaidi *et al.*, 2021) [13]. A typical machine learning workflow proceeds through six stages: data collection from structured sources such as spreadsheets or unstructured sources such as images; data pre-processing to handle missing values, remove noise and normalise scales; selection of an appropriate model, for example a decision tree, a support vector machine or a neural network; training of the model on historical data so that its internal parameters minimise prediction error; testing of the trained model on data it has not previously seen, using metrics such as accuracy, precision, recall or mean squared error; and finally, deployment of the validated model to make predictions or automate decisions in a live setting. Figure 1 shows the

hierarchical relationship between Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and Neural Networks (NNs). An illustrative example from the poultry sector is provided by Birzniece *et al.* (2022) [14], who used a long short term memory neural network to forecast broiler body weight from environmental variables, including temperature, gas concentration, humidity and feed consumption. The model achieved a three-day forecast horizon with a root mean square error (RMSE) of 0.295, demonstrating that environmental and feeding data alone can support short horizon weight prediction with useful accuracy.

2.4 Deep learning and neural network architecture

Deep learning is a subset of machine learning that relies on artificial neural networks (ANN) with many processing layers to model complex, non-linear relationships (Sarker, 2021) [1]. Rather than requiring an analyst to manually specify which features of an image or a sound recording are important, a deep network learns useful representations directly from raw data, which is one reason it performs so well on image and sound-based tasks such as those described in section 4.

The basic computational unit of any neural network is the node, loosely analogous to a biological neuron. As illustrated in Figure 2, information enters at an input layer, passes through one or more hidden layers where it is combined and transformed by weighted connections, and finally produces a result at an output layer. During training, the network is shown many labelled examples, for instance images of healthy and diseased birds, and the connection weights are progressively adjusted so that the network's predictions increasingly match the known labels.

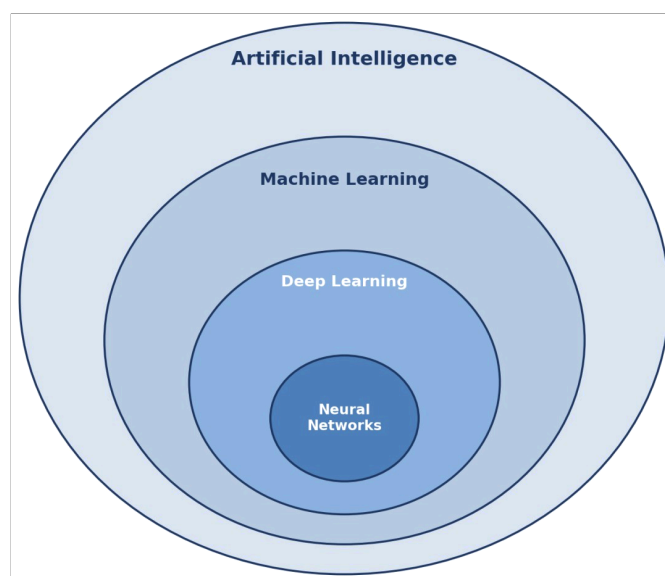


Figure 1. Conceptual hierarchy of artificial intelligence, showing machine learning, deep learning and neural networks as progressively narrower subsets.

Three neural network architectures recur throughout the literature. The artificial neural network (ANN) is the general, fully connected form described above and is well suited to tabular prediction problems such as estimating a nutrient requirement from a small number of numeric inputs. The convolutional neural network (CNN) applies a series of learned filters that scan across an image and is the architecture of choice for tasks involving photographs or video frames, such as bird identification, body condition scoring and faecal image classification. The recurrent neural network (RNN), and particularly its long short-term memory (LSTM) variant, is designed to handle sequential or time ordered data, such as a series of daily feed intake or body weight readings, and is therefore favoured for forecasting tasks.

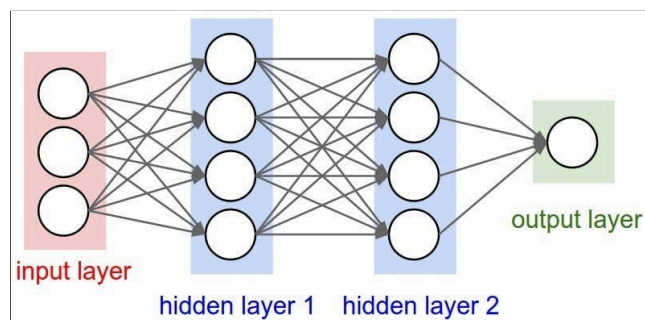


Figure 2. Schematic structure of an artificial neural network, showing an input layer, two hidden layers and an output layer connected by weighted links.

3. Advantages of artificial intelligence in poultry nutrition

Before considering individual applications in detail, it is useful to summarise, at a general level, why the poultry nutrition sector has become such fertile ground for artificial intelligence. Five recurring benefits emerge from the literature reviewed in this article.

- **Precision feed formulation.** Machine learning models can analyse large historical datasets on ingredient composition, cost and bird performance simultaneously, and can adjust predicted optimal diets in near real time as ingredient quality varies, which is difficult to achieve with static, linear formulation approaches alone.
- **Real time monitoring of health and nutrition.** Computer vision and Internet of Things sensors continuously track feed intake, water consumption and body weight, which allows nutritional deficiencies or early disease signs to be flagged before they translate into measurable production losses.
- **Predictive analytics.** Because AI models can forecast future performance or flag deviations from expected growth curves, farmers are able to intervene proactively, for example by adjusting feed allocation, rather than reacting only after a problem has already affected flock uniformity.
- **Biosecurity.** Automated and robotic feeding systems reduce the frequency and duration of human entry into poultry houses, lowering the risk of introducing pathogens, while AI driven cameras can detect early behavioural signs of disease and support rapid isolation of affected birds.
- **Environmental control.** Smart sensor networks linked to AI based controllers regulate temperature, humidity, ventilation and lighting in real time, and can detect harmful gases such as ammonia and carbon dioxide, helping to maintain conditions that support efficient nutrient utilisation.

4. Applications of artificial intelligence in poultry nutrition

The applications reviewed below are organised along the feed to bird value chain, beginning with the screening of raw ingredients and ending with the individualised feeding of live birds. Figure 3 summarises how these domains relate to one another. Within each subsection, the underlying method is described first, followed by the quantitative performance reported in the primary literature and, where relevant, the practical merits and limitations noted by the original authors.

4.1 Screening feed ingredients for mycotoxin contamination

Contamination of maize and other cereal ingredients with mycotoxin producing fungi remains a persistent threat to poultry health and productivity, and conventional laboratory confirmation, typically by chromatography or immunoassay, is too slow and too costly to be applied to every incoming consignment on a commercial farm. Leo (2023) [2] addressed this gap by developing a smartphone based diagnostic tool built around a deep convolutional neural network. Image data were collected from maize growing regions of Tanzania, namely Arusha, Dodoma, Kagera and Mbeya, which together are among the country's principal maize producing and exporting areas and are also considered highly susceptible to mycotoxin infection. A total of 2400 images were captured, comprising 300 healthy and 300 mycotoxin affected maize samples from each region.

Three convolutional architectures, VGG16, ResNet152 and InceptionV3, were trained and compared on this dataset using validation accuracy, test accuracy, training time and loss as evaluation criteria. ResNet152 emerged as the best performing architecture, achieving an average classification accuracy of 99.7 percent, and was subsequently deployed inside a mobile phone application through which farmers could photograph a maize sample and receive an immediate contamination assessment. In a field validation exercise involving farmers, maize traders, information technology specialists, government decision makers and policymakers, 89 percent of participants agreed that the tool was effective for detecting mycotoxin contamination under real world conditions.

Liu *et al.* (2025) [15] combined near infrared spectroscopy with four machine learning classifiers, namely partial least squares discriminant analysis, a back propagation neural network, a support vector machine and a random forest, to detect microplastic contamination in chicken feed. After the characteristic wavelengths most informative for classification were selected using a successive projections algorithm, a support vector machine model built on those wavelengths correctly classified contaminated and uncontaminated feed samples in an independent test set with an accuracy of 96.26 percent. Because microplastic contamination of feed ingredients is increasingly recognised as an emerging food safety concern, this study indicates that the same spectroscopy plus machine learning approach already used for mycotoxin screening can be extended to a wider range of physical and chemical feed hazards, without requiring a separate piece of laboratory equipment for each contaminant type.

4.2 The Internet of Things as a data foundation

Many of the applications described in this literature depend on an underlying layer of networked sensors, generally referred to as the Internet of Things (IoT). The Internet of Things refers to interconnected physical devices, embedded with sensors, software and communication hardware, that collect and exchange data over a network, supporting improved efficiency, decision making and automation across domains including agriculture (Da Xu *et al.*, 2014) [16]. Cameras, microphones, radio frequency identification readers, load cells and gas sensors all function as the data gathering front end for the AI models discussed below, converting physical parameters such as temperature, humidity, motion or sound pressure into the digital signals that machine learning algorithms require as input.

4.3 Computer vision in poultry nutrition and management

Computer vision is the branch of artificial intelligence concerned with enabling computers to interpret images and video in ways that approximate human visual perception (Voulodimos *et al.*, 2018) [17]. Within poultry nutrition and management, computer vision has been applied to at least five distinct tasks, summarised below.

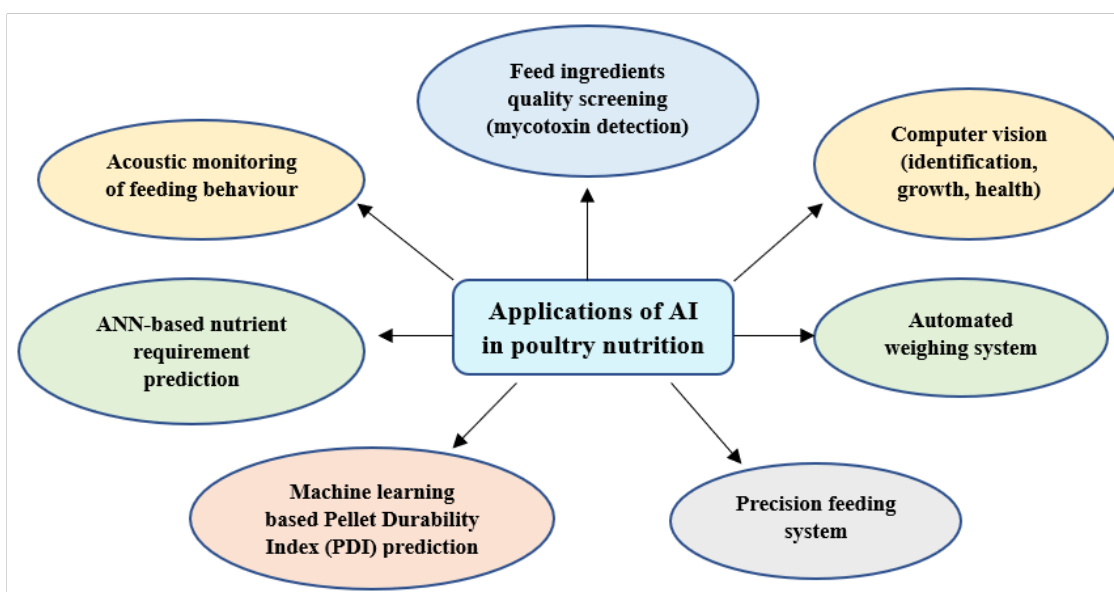


Figure 3. Overview of the principal domains in which artificial intelligence is applied across the poultry nutrition value chain, from raw material screening to individualised precision feeding.

4.3.1 Identification and traceability of individual birds

Conventional identification methods, such as wing bands or leg bands, are labour intensive to apply and can cause measurable stress to birds. Deep learning-based computer vision offers a non-contact alternative: convolutional architectures, including general purpose CNNs, YOLO based detectors and ResNet variants, can distinguish individual birds from feather pattern, body size and other morphological features, with the resulting identity linked to a continuously updated digital profile (Okinda *et al.*, 2020) [6]. Where radio frequency identification tags are also fitted, the two technologies can be combined to further improve identification accuracy. The principal benefits are a reduction in manual labour, improved traceability of individual growth and health records, and the ability to support genuinely individualised, rather than pen average, precision feeding.

4.3.2 Real time growth monitoring

Body weight can be estimated from images by extracting linear dimensions such as height, width and body area and the accuracy of this approach is improved substantially when three dimensional cameras or light detection and ranging (LiDAR) sensors are used to build a depth map of the bird rather than relying on a single two-dimensional image (Mortensen *et al.*, 2016) [18]. Because the bird need not be caught or handled, this method avoids the stress associated with manual weighing and allows growth variation within a flock to be detected earlier, so that underperforming individuals can be identified for corrective management.

4.3.3 Real time feed conversion ratio monitoring

Cameras equipped with motion detection algorithms and pose estimation techniques can track pecking and ingestion behaviour directly, and when this information is combined with continuously updated, vision derived body weight data, an estimate of feed conversion ratio can be generated without interrupting normal feeding activity (Okinda *et al.*, 2020) [6]. This provides nutritionists with much more granular feed efficiency data than periodic manual weighing, supports earlier detection of inefficient feeders or incipient disease and can meaningfully reduce feed cost through more precisely targeted diet adjustment.

4.3.4 Feeding and drinking behaviour analysis

Continuous video analysis allows the frequency, duration and timing of feeding and drinking bouts to be logged automatically, with automated alerts generated whenever intake patterns deviate from an expected baseline, for example a sudden reduction in feeding activity that may indicate illness. Beyond disease surveillance, this informa-

tion helps managers optimise the physical placement of feeders and drinkers and reduces feed wastage associated with poor accessibility.

4.3.5 Posture, health and faecal image analysis

Deep learning-based gait and posture analysis can detect abnormalities such as depressed bird posture, wing drooping or uneven weight bearing, which are early indicators of lameness, tibial dyschondroplasia or other locomotor disorders, while thermal and infrared imaging can reveal heat stress, fever or circulatory abnormalities that are not visible to the naked eye (Aydin, 2017) [19]. Collectively, these tools support earlier disease detection, reduced economic loss from delayed intervention and improved welfare monitoring at a scale that would not be practical using human observation alone.

A particularly instructive example of computer vision applied to poultry health, with direct nutritional relevance because it underpins early intervention decisions, is the faecal image classification system developed by Machuve *et al.* (2022) [20]. The authors trained four convolutional neural network architectures, VGG16, InceptionV3, MobileNetV2 and Xception, to distinguish healthy faecal samples from those associated with Newcastle disease, salmonellosis and coccidiosis. The training dataset comprised 6812 farm collected and 1255 laboratory collected faecal images, split 80:20 for training and testing, with a further 15 percent of the training data reserved for validation.

As summarised in Figure 4, MobileNetV2 and Xception achieved the highest classification accuracies, at 98.02 percent and 98.24 percent respectively, outperforming the older VGG16 and InceptionV3 architectures. Because MobileNetV2 and Xception are also comparatively lightweight networks, both were considered suitable for deployment on smartphones, giving farmers a rapid, non-invasive screening tool that they can use in the field to decide whether a bird requires closer veterinary or nutritional attention.

Two further studies published in 2025 extend this line of work in directions that are particularly relevant to resource constrained poultry operations. Islam *et al.* (2025) [21] revisited the faecal image classification problem addressed by Machuve *et al.* (2022) [20], but replaced the deep convolutional networks used in that study with a lightweight pipeline that extracts colour features from three colour spaces, red green blue, hue saturation value and LAB, and feeds a compact, selected feature set into a simple artificial neural network classifier. This lightweight model achieved a classification accuracy of 95.85 percent while requiring no graphics processing unit, indicating that near state of the art disease screening accuracy can be delivered on the low-cost hardware already available to most smallholder and mid-sized poultry farms, rather than only on the specialised computing infrastructure that deep convolutional networks typically require. In a

complementary application, Ansarimovahed *et al.* (2025) [22] used object detection to isolate the head and leg regions of birds in thermal infrared images and applied machine learning classifiers to the resulting temperature patterns to predict the presence of avian influenza

and Newcastle disease, illustrating how thermal imaging can extend AI based surveillance from general posture and gait abnormalities to specific, notifiable viral diseases with direct implications for flock nutrition and welfare management.

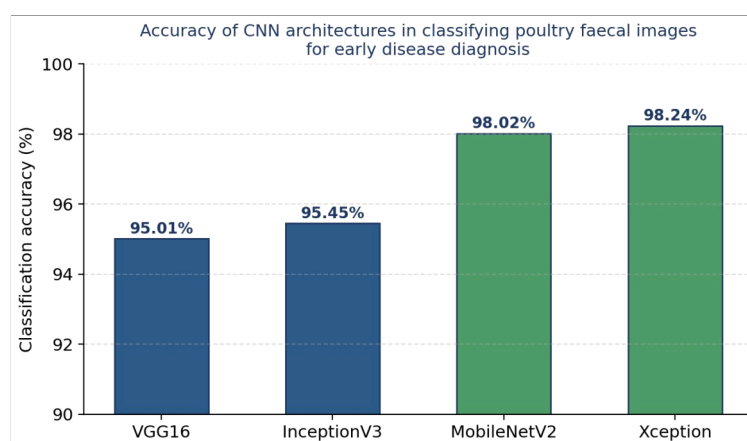


Figure 4. Comparative classification accuracy of four convolutional neural network architectures for distinguishing healthy and diseased poultry faecal images. Data redrawn from Machuve *et al.* (2022) [20].

4.4 Automated poultry weighing systems

Automated poultry weighing systems use load cell sensors mounted on a platform to record the weight of birds as they step onto it voluntarily. The load cell converts mechanical force into an electrical signal, which a microcontroller filters to remove noise; when several birds are present simultaneously, time-based filtering, statistical analysis and machine learning algorithms are used to separate and attribute individual weight readings. Resulting data are logged and transmitted to a farm dashboard or cloud platform for real time review. Automatic poultry weighing platforms are typically installed by suspending a scale from the house ceiling so that it can be disconnected easily for cleaning, and a single control computer can manage one or two scales covering one or two houses. Such systems commonly report average weight, number of individual weighing recorded, daily gain, standard deviation, coefficient of variation and uniformity, growth day and separate male and female weight trends, with data retained for periods of up to 500 days.

Zhou *et al.* (2023) [23] reported a commercially deployed automated weighing platform achieving an average accuracy of 99.5 percent with a standard deviation of 2.3 percent relative to manual reference weighing, confirming that these systems can approach the accuracy of manual weighing while removing the handling stress and labour cost associated with it. Reported operational benefits include earlier warning of illness, evident as reduced daily gain or a falling number of weighing events, continuous visibility of flock uniformity and variation relative to a target growth curve, rapid assessment of the performance impact of a new feed batch, and elimination of manual weighing labour.

4.5 Acoustic monitoring of feeding behaviour

Sound based monitoring offers a further non-invasive route to characterising feeding behaviour. Aydin *et al.* (2016) [5] recorded the pecking sounds of ten 39 day old male broiler chickens using a microphone mounted on a commercial feeder, connected through a preamplifier to a computer and sampled at 44.1 kilohertz with 16 bit resolution, while a parallel automated weighing system recorded feed uptake as a reference standard. An algorithm identified individual pecking events within the continuous audio stream, restricted to a frequency band of approximately 1000 to 5000 hertz, and used the count of detected pecks to estimate feed intake, meal size, meal duration, number of meals per day and feeding rate.

The feed intake per peck was fixed at 0.025 grams based on prior calibration work (Aydin *et al.*, 2014) [24], and total feed intake for an observation period was calculated as the product of feed intake per peck

and the number of pecks recorded in that period. Feeding rate and meal size were derived analogously, using the number of pecks per minute and the number of pecks per meal respectively, with individual meals identified from the start and end times of clusters of pecking events. Agreement between the acoustic estimates and the reference weighing and video-based methods was assessed using the Pearson product moment correlation coefficient, and strong positive correlations were obtained across all measures, at 0.929 for feed intake, 0.884 for meal size, 0.947 for number of meals, 0.969 for meal duration and 0.994 for feeding rate.

The authors highlighted several practical merits of the acoustic approach: it is inexpensive and can be tested directly under commercial farm conditions, it is entirely non-invasive, it requires minimal human presence during monitoring, which supports bird welfare, and it can operate continuously across the full life of a flock. Its principal limitation is that when many birds feed simultaneously, overlapping pecking sounds of similar amplitude and frequency are difficult to separate accurately, and factors such as age, strain and pathological state can alter the acoustic signature of pecking, which may require the underlying algorithm to be recalibrated for different production contexts.

4.6 Artificial neural network prediction of amino acid requirements

Methionine is widely recognised as the first limiting amino acid in most practical poultry diets, and because of the sparing relationship between methionine and cysteine, methionine supplementation is commonly used to meet the total sulphur amino acid requirement of growing birds (Bunchasak, 2009) [25]. Nutrient requirements for amino acids such as these have traditionally been estimated using regression analysis, but this approach requires a pre specified mathematical form, typically linear or quadratic, to be imposed on the underlying dose response relationship. Artificial neural networks offer an alternative that does not require the analyst to assume a functional form in advance.

Kaewtapee *et al.* (2021) [26] compared a radial basis function ANN with conventional quadratic regression for predicting the total sulphur amino acid requirement of broiler chickens during the starter period, days 1 to 10, and the grower period, days 11 to 21. A total of 560 male Ross 308 broiler chicks were allocated across 28 replicate pens and fed basal diets supplemented with methionine to achieve four total sulphur amino acid concentrations in each period, namely 0.78, 1.25, 1.30 and 1.36 percent in the starter phase and 0.54, 0.90, 0.95 and 1.00 percent in the grower phase. Average daily gain was recorded per pen at the end of each period, and a bootstrapping procedure was used to expand the original 28 observations into 280

pseudo-observations, of which 220 were used for model training and 60 for testing. The ANN itself comprised a single input node representing the total sulphur amino acid level, one hidden layer with three nodes, and a single output node representing average daily gain.

As shown in Figure 5, the optimum total sulphur amino acid level predicted by the ANN was 1.13 percent in the starter period and 0.99 percent in the grower period, compared with 1.20 percent and 0.97 percent predicted by quadratic regression, and the ANN model predicted a numerically higher maximum average daily gain than the regression model in both periods, at 18.21 grams versus 17.95 grams in the starter phase and 52.73 grams versus 52.65 grams in the grower phase. Model fit statistics reported by the authors further favoured the ANN, which achieved higher coefficients of determination, at 0.7294 and 0.8097 in the starter and grower periods respectively, together with lower mean absolute deviation, mean absolute percentage error and mean square error than the corresponding regression models. These results support the conclusion that ANN based approaches can offer a more flexible and, in this instance, more accurate alternative to classical regression for amino acid requirement estimation.

4.7 Machine learning prediction of pelleted feed quality

Pelleting is widely used to improve the nutrient digestibility, feed consumption and palatability of poultry diets, largely as a result of starch gelatinisation and protein hydrolysis that occur during conditioning and compression (Muramatsu *et al.*, 2015) [27]. The pellet durability index (PDI) quantifies the ability of a pelleted feed to withstand the mechanical stress of handling and transport without excessive fragmentation, and predicting PDI in advance, from formulation and processing parameters, would allow feed millers to adjust settings before a batch is produced rather than only measuring quality afterwards.

You *et al.* (2022) [3] evaluated twelve machine learning regression algorithms for this purpose, listed in Table 3, using a dataset of 2471 observations collected over eight months from a commercial feed mill operated by Trouw Nutrition in Ontario, Canada. Sixteen input variables were used, spanning three categories: pellet manufacturing parameters, including order size, conditioning temperature, feeder speed, production line and operator; feed formulation parameters, including the dietary inclusion levels of wheat, bakery byproduct meal, dried distillers grains with solubles, corn, canola meal, soybean meal and added fat; and environmental parameters specific to the mill's location, including ambient temperature, humidity and atmospheric pressure. A five-fold cross validation procedure was used to screen

the twelve candidate algorithms, of which four were excluded because they showed clear evidence of overfitting or underfitting, leaving eight algorithms for detailed comparison on an independent test set.

Table 3. Machine learning regression algorithms evaluated for prediction of pellet durability index.

Index	Algorithm	Acronym
1	Ordinary least squares linear regression	LR
2	Adaptive boosting regression	ABR
3	Decision tree	DT
4	Gradient boosting regression	GBR
5	K nearest neighbour	KNN
6	Least absolute shrinkage and selection operator regression	LASSO
7	Linear support vector regression	LSVR
8	Multi-layer perceptron neural network	MLP
9	Random forest	RF
10	Ridge regression	RR
11	Support vector regression	SVR
12	Stacked regression	SR

Source: adapted from You *et al.* (2022) [3].

Support vector regression (SVR) emerged as the best individual performer, achieving the lowest mean absolute error, at 3.280, and the lowest mean square prediction error, at 16.192, on the test set, together with a comparatively high concordance correlation coefficient of 0.636. Stacked regression (SR), which combines predictions from multiple base learners, achieved a marginally higher concordance correlation coefficient of 0.643, indicating that model stacking can capture slightly more of the true variation in PDI than any single algorithm. The multi-layer perceptron neural network achieved the steepest regression slope between predicted and observed values, at 0.525, but its predictions were more widely scattered than those of SVR or SR, indicating higher variance. Taken together, these results indicate that SVR and SR are the more dependable choices for predicting pellet durability in a commercial feed milling context, and that machine learning based prediction of physical feed quality is achievable using routinely recorded formulation and processing records, without any need for additional laboratory analysis of the finished pellet.

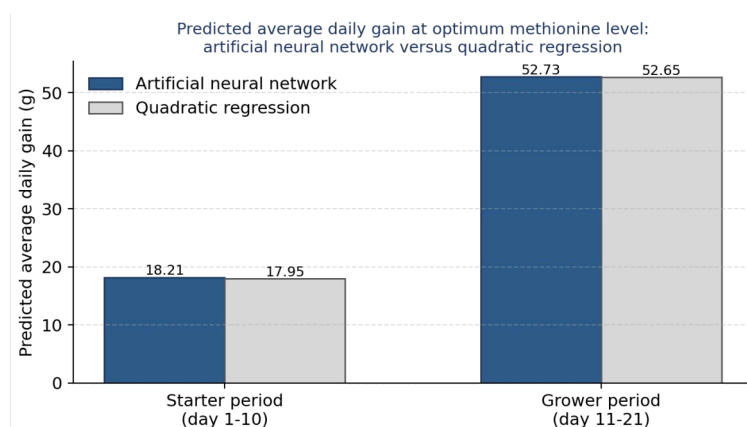


Figure 5. Comparison of average daily gain predicted by an artificial neural network model and a quadratic regression model at the optimum total sulphur amino acid level. Data redrawn from Kaewtapee *et al.* (2021) [26].

4.8 Deep learning prediction of dietary metabolic energy

Metabolic energy is among the most important, and most expensive to determine experimentally, nutritional characteristics of a compound feed, and Wang *et al.* (2023) [4] explored whether a deep learning approach could reduce this reliance on direct in vivo assay. The authors

developed a long short term memory network with a three-layer architecture, an input layer, a hidden layer tested with 5, 10 and 20 nodes, and an output layer, trained on formulations built from ten raw materials, namely corn, soybean cake, rice bran cake, meat and bone meal, lysine, methionine, stone flour, calcium hydrogen phosphate,

premix and salt, with in vitro assay values used as the reference metabolic energy measurement.

As illustrated in Figure 6, the model tracked the observed metabolic energy values closely across the tested range, with the difference between predicted and observed metabolic energy varying from approximately 0.3 to 0.7 megajoules per kilogram and a fitting degree, defined by the authors as the closeness of predicted to observed values, consistently above 95 percent. The hidden layer configuration with 10

nodes produced the most accurate predictions as training iterations increased, suggesting that model capacity needs to be tuned rather than simply maximised. These findings indicate that, once trained on a sufficiently representative formulation history, an LSTM model can provide feed millers with a fast, low cost first estimate of dietary metabolic energy that could complement, though not yet fully replace, conventional in vivo determination.

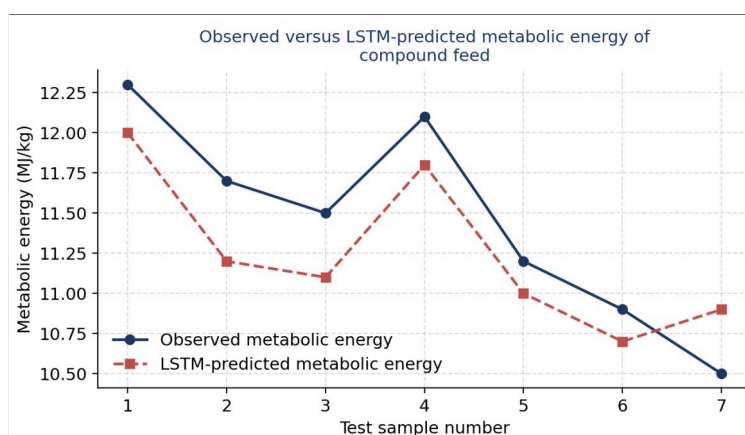


Figure 6. Agreement between observed metabolic energy values and values predicted by a long short-term memory (LSTM) neural network. Data redrawn from Wang *et al.* (2023) [4].

4.9 Artificial intelligence based precision feeding

Precision nutrition is the practice of matching the nutrient supply of individual animals as closely as possible to their actual requirements, with the aim of safe, high quality, efficient production and minimal

environmental burden (Frost *et al.*, 2003) [28]. In poultry, this concept is often summarised through four linked principles: delivering the right amount of feed, with the right nutrient composition, in the right proportion relative to the bird's requirement, and at the right time.

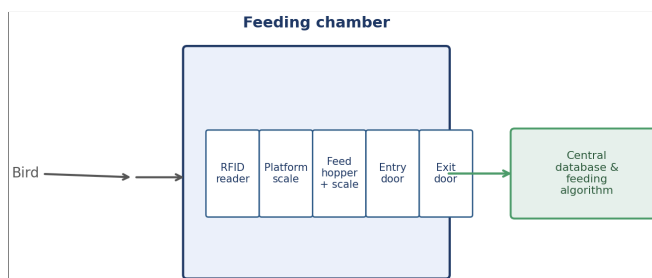


Figure 7. Simplified schematic of an artificial intelligence enabled precision feeding station, showing sequential identification, weighing and individualised feed dispensing of birds, with all visit data logged to a central database. Redrawn and adapted from the concept described by Zuidhof *et al.* (2017) [7].

Zuidhof *et al.* (2017) [7] operationalised these principles in a prototype precision feeding station developed at the University of Alberta, in which a single station served ten broiler breeder pullets between 35 and 140 days of age. The feeding chamber, illustrated schematically in Figure 7, combined seven functional elements: an entry door permitting access to one bird at a time, an exit door, a radio frequency identification reader, a platform scale accurate to five grams for weighing birds up to ten kilograms, a feed hopper fitted with a scale accurate to 0.1 grams, a feeder door controlling access to feed, and a mechanism to gently eject a bird from the chamber once its visit was complete. Each time a bird entered the station, the system logged the date and time of entry and exit, the bird's identity and body weight, the mass of feed present before and after the visit, the resulting meal size and running totals of the number of meals and total daily feed intake for that bird.

The control algorithm compared each bird's measured body weight against a target growth curve: birds below their target curve were offered feed and consumed a meal, whereas birds that had already reached or exceeded their target weight were identified and ejected from the station without receiving feed, so that no unnecessary energy or nutrients were provided to birds that did not require them. Because every visit was individually logged with a radio frequency identification tag, the system also revealed marked differences in the diet feeding pattern of different birds within the same flock. One bird visited the station almost exclusively during the dark, lights off period, indicating a preference for nocturnal feeding, a second visited almost exclusively while lights were on, and a third visited the station throughout both the light and dark periods, which the authors interpreted as evidence of greater behavioural assertiveness relative to its flock mates. The most striking production outcome of the trial was its effect on flock uniformity: the coefficient of variation in body weight fell

from close to 14 percent before the intervention to below 2 percent by the end of the study, a level of uniformity that the authors noted had not previously been reported in broiler breeder flocks, underscoring the potential of individualised, AI supported feeding to resolve a long-standing challenge in breeder flock management.

5. Challenges and limitations

Despite the promising results summarised above, the routine adoption of artificial intelligence in poultry nutrition, particularly outside large integrated commercial operations, remains constrained by several practical factors.

- **High initial cost.** Sensors, cameras, computing infrastructure and the software licences or subscriptions associated with AI based platforms represent a substantial upfront investment that may be difficult to justify for small and medium scale poultry enterprises, even where the technology would eventually pay for itself through improved efficiency.
- **Data dependency and accuracy.** The predictive quality of any machine learning or deep learning model is bounded by the quality, volume and representativeness of the data used to train it. Inconsistent sensor calibration, missing records or data can all lead to inaccurate recommendations, with corresponding risks to bird health and productivity.
- **Technical expertise requirements.** Installing, calibrating and interpreting the output of AI based systems requires a level of technical literacy that many farmers and even some nutrition professionals do not yet possess and this training gap is often more acute in regions with limited access to technical support.
- **Ethical and privacy concerns.** Continuous camera, audio and sensor-based monitoring generates large volumes of farm level data, raising legitimate questions about who owns that data, how it may be used or resold by technology providers and how farm level information should be protected from misuse by third parties.
- **Access and connectivity.** Many of the applications reviewed here depend on reliable internet connectivity for cloud-based data processing and remote monitoring and such connectivity remains inconsistent in a number of rural poultry producing regions. These constraints are consistent with [Ajibola et al. \(2025\) \[29\]](#) assessment of on farm AI adoption in poultry welfare monitoring under real farm conditions.

6. Future perspectives and directions

Integration of AI based nutritional tools with genomic, metabolomic and microbiome data, so that predicted nutrient requirements or feeding strategies can be combine not only to a bird's real time growth and behaviour, but also to its underlying genetic potential and gut microbial profile. [Lo Presti \(2026\) \[30\]](#) suggests that the next step in poultry nutrition is to combine AI with advanced technologies such as genomics, metabolomics and microbiome analysis. This would allow AI to predict the bird's nutrient requirements using real time performance, feed quality and the bird's own biological information, supporting more personalized and precise feeding.

[Abdel-Wareth et al. \(2026\) \[31\]](#) described an AI based precision nutrition system in poultry that continuously monitor feed intake, bird growth and farm conditions, and use this information to automatically adjust poultry diets. YOLOv8 based bird counting achieved about 93% precision and recall, demonstrating its potential for real time precision nutrition.

7. Conclusions

Artificial intelligence has moved from being a future concept to a practical tool in poultry nutrition. Deep learning can classify feed and faecal images with high accuracy, while computer vision and acoustic sensors can monitor feeding behaviour and body weight effectively.

Machine learning can also help predict nutrient requirements, pellet quality and metabolizable energy with performance comparable to or better than traditional methods. Precision feeding can further improve flock uniformity. However, wider adoption is limited by high costs, poor data quality, lack of trained personnel, privacy issues and limited rural connectivity. Therefore, future progress will depend not only on better AI models but also on developing affordable, reliable and practical systems suitable for real farm conditions.

References

1. Sarker IH. Deep learning: A comprehensive overview on techniques, taxonomy, applications and research directions. *SN Computer Science*. 2021;2(6):420.
2. Leo J. Segmentation of mycotoxin's contamination in maize: A deep learning approach. *Informatics in Medicine Unlocked*. 2023;39:101248.
3. You J, Tulpan D, Malpass MC, Ellis JL. Using machine learning regression models to predict the pellet quality of pelleted feeds. *Animal Feed Science and Technology*. 2022;293:115443.
4. Wang H, Liu J, Dong Z, Song J, Zhu Z. Artificial intelligence-based metabolic energy prediction model for animal feed proportioning optimization. *Italian Journal of Animal Science*. 2023;22(1):942-952.
5. Aydin A, Berckmans D. Using sound technology to automatically detect the short-term feeding behaviours of broiler chickens. *Computers and Electronics in Agriculture*. 2016;121:25-31.
6. Okinda C, Nyalala I, Korohou T, Okinda C, Wang J, Achieng T, Wamalwa P, Mang T, Shen M. A review on computer vision systems in monitoring of poultry: A welfare perspective. *Artificial Intelligence in Agriculture*. 2020;4:184-208.
7. Zuidhof MJ, Fedorak MV, Ouellette CA, Wenger II. Precision feeding: Innovative management of broiler breeder feed intake and flock uniformity. *Poultry Science*. 2017;96(7):2254-2263.
8. Kaplan A, Haenlein M. Siri, Siri, in my hand: Who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. *Business Horizons*. 2019;62(1):15-25.
9. Asif M, Gouqing Z. Innovative application of artificial intelligence in a multi-dimensional communication research analysis: A critical review. *Discover Artificial Intelligence*. 2024;4(1).
10. Bostrom N. *Superintelligence: Paths, dangers, strategies*. Oxford University Press; 2014.
11. Russell S, Norvig P. *Artificial intelligence: A modern approach* (4th ed.). Pearson; 2021.
12. Goertzel B. Artificial general intelligence: Concept, state of the art, and future prospects. *Journal of Artificial General Intelligence*. 2014;5(1):1-48.
13. Alzubaidi L, Zhang J, Humaidi AJ, Al-Dujaili A, Duan Y, Al-Shamma O, Farhan L. Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions. *Journal of Big Data*. 2021;8:1-74.
14. Birzniece I, Andersone I, Nikitenko A, Balina S, Kikans A. Time series forecast model application for broiler weight prediction using environmental factors. In 2022 International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME). 2022:1-7.
15. Liu Y, Huo Z, Huang M, Yang R, Dong G, Yu Y, Lin X, Liang H, Wang B. Rapid detection of microplastics in chicken feed based on near infrared spectroscopy and machine learning algorithm. *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy*. 2025;329:125617.
16. Da Xu L, He W, Li S. Internet of things in industries: A survey. *IEEE Transactions on Industrial Informatics*. 2014;10(4):2233-2243.
17. Voulodimos A, Doulamis N, Doulamis A, Protopapadakis E. Deep learning for computer vision: A brief review. *Computational Intelligence and Neuroscience*. 2018;2018(1):7068349.

18. Mortensen AK, Lisouski P, Ahrendt P. Weight prediction of broiler chickens using 3D computer vision. *Computers and Electronics in Agriculture*. 2016;123:319-326.
19. Aydin A. Using 3D vision camera system to automatically assess the level of inactivity in broiler chickens. *Computers and Electronics in Agriculture*. 2017;135:4-10.
20. Machuve D, Nwankwo E, Mduma N, Mbelwa J. Poultry diseases diagnostics models using deep learning. *Frontiers in Artificial Intelligence*. 2022;5:733345.
21. Islam AKMS, Hassan MR, Uddin M, Rahman MS. Lightweight model for poultry disease detection from fecal images using multi-color space feature optimization and machine learning. *arXiv preprint*. 2025;arXiv:2507.10056.
22. Ansarimovahed A, Banakar A, Li G, Javidan SM. Separating chickens' heads and legs in thermal images via object detection and machine learning models to predict avian influenza and Newcastle disease. *Animals*. 2025;15.
23. Zhou D, Zhou Y, He P, Yu L, Pan J, Chai L, Lin H. Development of an automatic weighing platform for monitoring body weight of broiler chickens in commercial production. *Frontiers of Agricultural Science and Engineering*. 2023;10(3):363-373.
24. Aydin A, Bahr C, Viazzi S, Exadaktylos V, Buyse J, Berckmans D. A novel method to automatically measure the feed intake of broiler chickens by sound technology. *Computers and Electronics in Agriculture*. 2014;101:17-23.
25. Bunchasak C. Role of dietary methionine in poultry production. *The Journal of Poultry Science*. 2009;46(3):169-179.
26. Kaewtapee C, Khetchaturat C, Nukreaw R, Krutthai N, Bunchasak C. Artificial neural networks approach for predicting methionine requirement in broiler chickens. *The Thai Journal of Veterinary Medicine*. 2021;51(1):161-168.
27. Muramatsu K, Massuquetto A, Dahlke F, Maiorka A. Factors that affect pellet quality: A review. *Journal of Agricultural Science and Technology*. 2015;9:717-722.
28. Frost AR, Parsons DJ, Stacey KF, Robertson AP, Welch SK, Filmer D, Fothergill A. Progress towards the development of an integrated management system for broiler chicken production. *Computers and Electronics in Agriculture*. 2003;39(3):227-240.
29. Ajibola G, Kilders V, Erasmus MA. A peep into the future: Artificial intelligence for on-farm poultry welfare monitoring. *Animal Frontiers*. 2025;14(6):72-75.
30. Lo Presti V. Innovative techniques for the evaluation and optimization of sustainable feeds in poultry nutrition: A critical integrative review of advanced analytical approaches, omics, and artificial intelligence. *Applied Sciences*. 2026;16(17):8373.
31. Abdel-Wareth AAA, Ahmed AA. Advancing poultry nutrition: AI innovations for sustainable nutrient requirements of poultry: A review. *Agriculture*. 2026;16(4):450.

How to cite this article: Raut L, Ponshe T, Khobragade TP, Singh D. Applications of artificial intelligence in poultry nutrition: A comprehensive review. *International Journal of Advanced Biochemistry Research*. 2026;10(9):623-631. doi: <https://www.doi.org/10.33545/26174693.2026.v10.i9h.10120>