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Egg Fertility Detection and Classification of an IoT-based Egg Incubation System using Transfer Learning: A CNN-based Approach

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Dear Editor-in- Chief,

I am writing to submit my manuscript entitled "**Egg Fertility Detection and Classification of an IoT-based Egg Incubation System using Transfer Learning: A CNN-based Approach**" for consideration for publication in **Food Control Journal.**

I want to emphasize that the authors declare that they have no conflicts of interest to report regarding the present study. The research presented in this manuscript is conducted with the utmost integrity and adherence to ethical standards.

Thank you for considering my submission. I look forward to your positive response.

Sincerely,

Mohammad Mehedi Hassan

Egg Fertility Detection and Classification of an IoT-based Egg Incubation System using Transfer Learning: A CNN-based Approach

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Abstract

This paper develops an IoT-based incubation system using a Convolutional Neural Network (CNN)-based egg fertility detection and classification model. To enhance large-scale production of healthy chicks, researchers are focusing on artificial incubation systems. One of the major and vital factors in incubation is egg fertility detection, known as egg candling during the incubation period. Traditional methods of egg candling are labor-intensive and often inaccurate, leading to the potential damage of fertile eggs by cracked infertile ones, which can cause the embryo to die. To ensure a better hatching rate in an artificial egg incubator, egg fertility detection and classification must be conducted precisely. To address these issues, this research develops a CNN-based egg fertility detection and classification model on an IoT-based egg incubation system. A total of 640 egg still pictures have been collected from a poultry firm during the incubation period, resulting in an EFD_Data_Set of

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1. Introduction

The poultry industry in Bangladesh plays a crucial role in the country's economic development, as a substantial portion of the population relies on it, either directly or indirectly [1]. One of the significant challenges facing this industry is meeting the substantial protein requirements through the large-scale production of healthy chicks. An automated egg incubator is a device that controls temperature, humidity, and related parameters automatically, enabling the large-scale production of chicks [2]. Several IoT-based egg incubation systems have been designed and developed to improve the efficiency and hatch rate of the incubation process [3, 4, 5, 6].

Various factors impact the successful development and hatching of chicks during egg incubation; egg candling is one of these crucial factors [7]. Egg candling is a process used to detect abnormalities and assess egg fertility during the seven-day period of incubation [8, 9]. Most incubation systems perform candling using a light source and manual methods, which are often insufficient for accurately classifying fertile and infertile eggs. Moreover, manual candling poses risks to the eggs, as it can expose fertile eggs to harmful viruses [10]. Manually removing eggs from the incubator to assess their growth, development, and fertility is also time-consuming and poses risks. To address these issues, several research strategies have been proposed to improve egg fertility detection and classification using machine learning and deep learning algorithms [11, 12, 13, 14, 15, 16, 17], each with varying success rates. In this paper, we design and develop an IoT-based incubation system that incorporates a Convolutional Neural Network (CNN)-based egg fertility detection and classification model.

Convolutional Neural Networks (CNNs) have demonstrated outstanding performance in various computer vision tasks, especially in image classification. The concept of transfer learning has further enhanced CNN applications by allowing the use of pre-trained models, eliminating the need for training from scratch and reducing the required size of the training dataset [18, 19, 20, 21, 22]. The research described in this paper proposes a CNN-based approach that incorporates an InceptionV3 model (a well-known pre-trained model) and transfer learning to maximize its capabilities for egg fertility detection and classification in an IoT-based egg incubation system, named InceptionV3-EFD. The primary goal of this study is to leverage transfer learning to enhance the InceptionV3 model for classifying egg fertility, enabling accurate and efficient identification of egg candling during the incubation period in a real-time egg incubation system. Here, transfer learning is used to capitalize on the pre-training approach, improving the generalizability of the proposed system. By implementing this approach, the training time is reduced, and the model's ability to accurately classify egg fertility patterns is improved.

The key contributions of this research are as follows:

- Development of a CNN-based deep learning model, named InceptionV3-EFD, using transfer learning.Â
- Creation of a unique dataset, EFD_Data_Set, by collecting real-time egg incubation images (i.e., during the candling period) from poultry farms.
- Design and implementation of an IoT-based system for detecting egg fertility.
- Training and testing of the proposed InceptionV3-EFD model using the created EFD_Data_Set.

The remaining sections of the paper are organized in the following manner: Section II provides a comprehensive summary of the relevant literature. Section III provides a comprehensive explanation of the study process, which encompasses the development of hardware and control systems for the IoT-based solution, the InceptionV3 architecture, and the transfer learning strategy. The details of these aspects are thoroughly discussed. The results are summarized in Section IV, while the concluding remarks include a description of the future focused effort and are presented in Section V.

2. Related Work

Over the years, researchers have made several attempts to classify egg fertility within incubation systems using various approaches. Many of these classification methods are based on well-established machine learning models. With the growing interest in deep learning, numerous strategies have been proposed to address the challenges of egg fertility detection. Researchers have developed systems for detecting fertilized eggs and managing incubation, incorporating automated temperature and humidity regulation along with image-based candling. One such system was designed using a microcontroller and programmed with LabVIEW, allowing it to autonomously regulate incubation conditions and perform candling via image processing [23].

In another approach, a prediction model using an artificial neural network (ANN) was proposed for detecting chicken egg fertility. This model was trained using Matlab R2018a's neural network toolbox, specifically the pattern recognition module. The model was fed 100 images, achieving a testing accuracy of 93.3% [13]. In a separate study, researchers employed the R-CNN model to assess egg maturity within an incubation system, reaching a classification accuracy of 80.5%. Additionally, they designed a user-friendly intelligent system with a graphical user interface (GUI) to facilitate real-time monitoring of egg condition and maturity within the incubator [11].

Another study combined a Back Propagation (BP) neural network with first-order statistical (FOS) feature extraction to gather information from embryonated eggs, aiming to distinguish fertile eggs from infertile ones. However, some egg images displayed similar patterns on the FOS platform, necessitating the modification or reduction of parameters within the BP neural network model. Testing was conducted with 100 data points, resulting in an 80% classification accuracy [17]. Shoffan et al. [12] explored chicken egg fertility detection using an SVM classifier with FOS feature extraction, processing 100 egg images. Their approach achieved an accuracy of 84.57%. They suggested that using a second-order feature extraction technique could potentially improve classification precision.

In an extension of their previous research, Shoffan and colleagues proposed the SVM-GLCM approach for detecting fertile and infertile eggs. This method utilizes the Gray-Level Co-occurrence Matrix (GLCM) technique, with six parameters: energy (En), variance (V), correlation (Cr), contrast (Ct), homogeneity (H), and entropy (Et). The dataset comprised 100 chicken egg images, evenly split between 50 fertile and 50 infertile samples, and achieved an average detection rate of 98.20% [16]. In another study, Kerim et al. [24] applied the Mask R-CNN technique with transfer learning to accurately identify viable and non-viable eggs. This study utilized a single deep learning model to perform detection, classification, and segmentation of viable and infertile eggs using images from an incubator.

To improve precision in poultry hatchery operations, CNN-transfer learning models have been employed for non-destructive chicken egg fertility detection. Models such as VGG16, ResNet50, InceptionNet, and MobileNet were trained and tested on a dataset of 200 single egg images, augmented through rotations, flips, scaling, translation, and reflection. These models consistently achieved high accuracy in classifying chicken egg fertility, with InceptionNet demonstrating the best performance across training and testing metrics, achieving 98% accuracy on the testing dataset [25].

It is noteworthy that most existing egg fertility detection and classification systems rely on relatively small datasets, and there is potential to improve model accuracy through additional tuning of network layers. An IoT-based system could provide poultry farmers with a more accurate, non-destructive solution for egg fertility detection. This research is thus motivated to achieve higher accuracy by integrating a CNN-based InceptionV3-EFD model with transfer learning and IoT capabilities, addressing the limitations of previous approaches.

3. Methodology

To design and develop an IoT-based automated egg fertility detection and classification system, we propose a CNN-based model integrated with IoT functionality. As an extension of our previous research [3], this model includes an automatic egg candling system incorporated into the previously proposed framework. In this section, we provide a comprehensive overview of our CNN-based egg fertility detection and classification process using the InceptionV3 architecture and transfer learning.

Figure 1 illustrates the proposed IoT-integrated machine learning model, where an ESP32 camera module is interfaced with an IoT-based egg incubation system. The entire system can autonomously evaluate egg fertility using a CNN-based model. For this study, a total of 640 egg images were collected over a seven-day incubation period from various poultry industries and rural

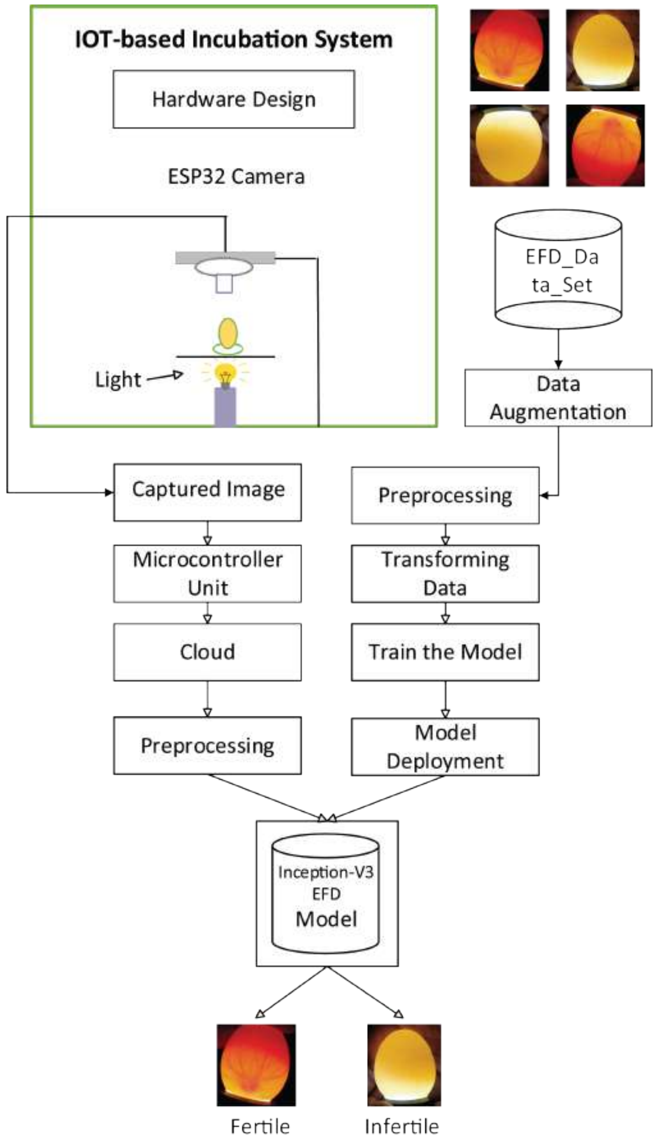

Figure 1: Proposed development model for the CNN-based egg fertility detection and classification.

poultry farms. The images were augmented through rotation, scaling, shifting, flipping, translation, and shearing to enrich the dataset. The augmented data was then filtered and processed into the correct input format for the pre-trained model. Finally, the data was fed into the proposed InceptionV3-

EFD model for training. In the IoT-based egg incubation system, captured images are transmitted to the cloud via a microcontroller unit, where they are pre-processed and analyzed by the trained model to detect egg fertility.

3.1. Hardware Design and Control System Development

In the hardware design, a cabinet structure was created to integrate all components of the egg incubation system in real-time and provide IoT services, as outlined in our previous research [3]. Figure 2 shows the physical layout of the real-time egg incubation system during the experiment. This system efficiently controls and monitors critical incubation factors such as temperature, humidity, and weight loss.

Figure 2: Physical structure of the proposed IoT-based Incubation System.

To control temperature and humidity, DS18B20 and DHT11 sensors are used, respectively. Two heaters are connected to regulate heat as needed, and a water chamber with a humidifier maintains humidity. Four fans circulate heat and humidity evenly throughout the incubator, ensuring that eggs remain at optimal temperature and humidity levels. To prevent embryos from adhering to the inner shell and to promote healthy growth, egg frames use a motorized system that rotates eggs at regular intervals. An additional backup system is incorporated to ensure reliable and uninterrupted power supply. The cabinet is constructed with durable materials that withstand high temperatures, are easy to clean, and offer long-term functionality. A 16x4 liquid crystal display (LCD) unit on the upper section of the cabinet provides real-time information on weight, temperature, humidity, and rotation status.

An ESP32 camera module is integrated to capture images of the eggs in the frame, which are then sent to the cloud for further processing and machine learning analysis. This module is positioned on the egg frame to capture real-time images at specific intervals, transmitting data to the cloud via a microcontroller. A small rechargeable torch light is placed beneath the egg frame to illuminate each egg for clear image capture. Eggs are arranged on a circular frame that rotates at regular intervals, positioning them beneath the ESP32 camera module for automated imaging.

During the seven-day period, the camera module is activated to detect and classify fertile and infertile eggs in the incubator. Initially, the camera module is initialized to capture current images of eggs in the frame, which are then sent to the cloud for processing. After pre-processing, the images are analyzed by the CNN model to detect and classify egg fertility. Each egg image is captured and classified sequentially. This proposed method involves multiple intricate steps, as illustrated in Figure 5.

3.2. Data Collection

In deep learning, a well-suited dataset is essential for effectively training a high-performance model. For this experiment, a dataset named EFD_Data_Set was created, consisting of 640 egg images. These images were collected from various poultry companies and rural chicken farms during the incubation period. Eggs typically reach maturity between days 6 and 7 of incubation, during which manual candling is performed to identify and separate infertile eggs. Our dataset was collected within this specific time frame, with eggs categorized into two groups: fertile and infertile. Figure 6 shows sample

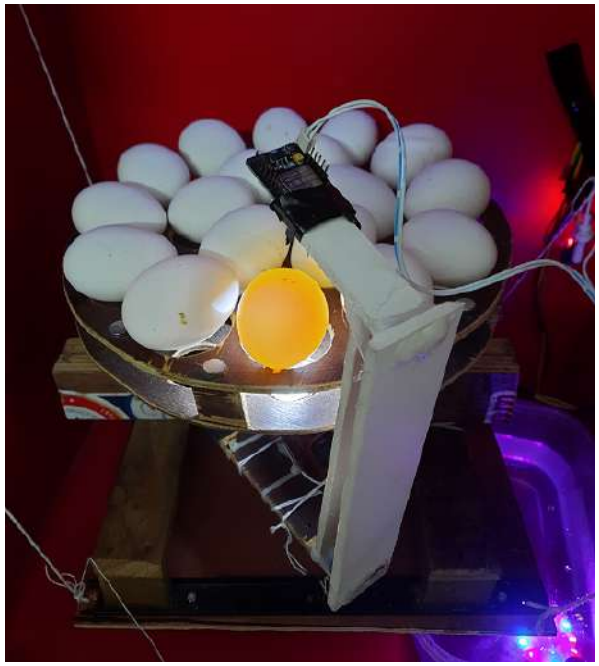

Figure 3: Hardware design of the proposed model for capturing images from the IoT-based Incubation System.

images from the fertile and infertile egg datasets, and Table 1 provides a description of the collected data.

Table 1: Description of Collected EFD_Data_Set

Classifier	**Images per Class**	**Augmented Images**	**Training Data (80%)**	**Validation Data (10%)**	**Test Data (10%)**
Fertile	310	2170	1736	217	217
Infertile	330	2310	1848	231	231
Total	640	4480	3584	448	448

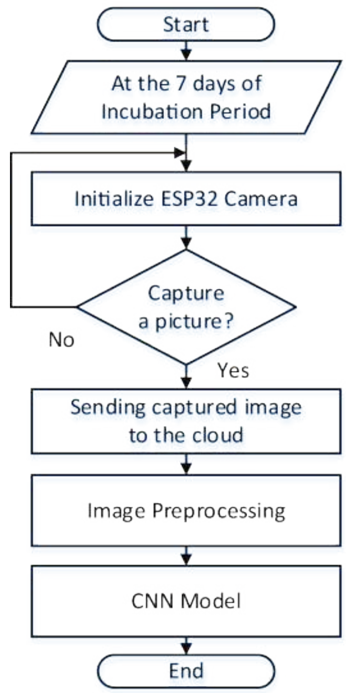

Figure 4: Flow chart of the control system for the camera module.

3.3. Data Augmentation

Data augmentation is a technique used to expand the training dataset, helping to reduce overfitting during model training [26, 27]. The images in our dataset contained noise and required adjustments in terms of dimensions and color. Therefore, we applied several data augmentation techniques, including rotation, scaling, shifting, flipping, translation, and shearing, to enhance the dataset and address overfitting issues.

3.3.1. Rotation

The egg images were randomly rotated within a specified angle range, introducing variations in egg orientation, which simulates different viewing angles observed during the candling process. This augmentation strategy improves the model's ability to learn and identify eggs from various perspectives.

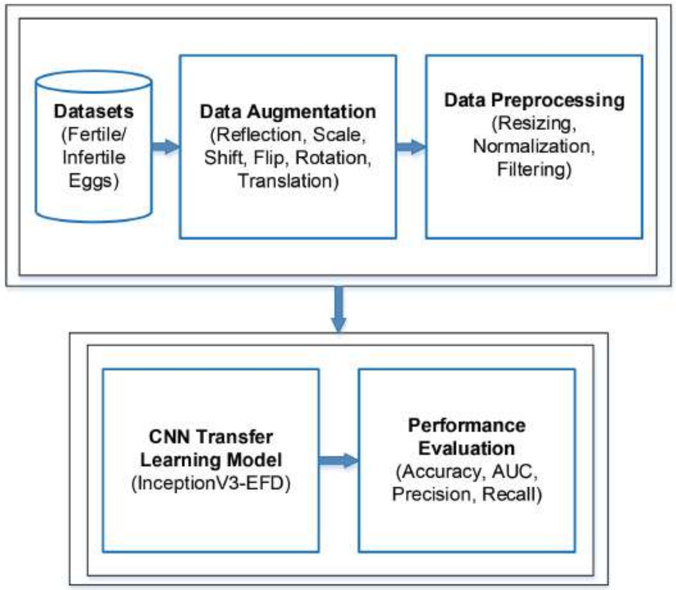

Figure 5: Workflow of the proposed InceptionV3-EFD model and its performance evaluation.

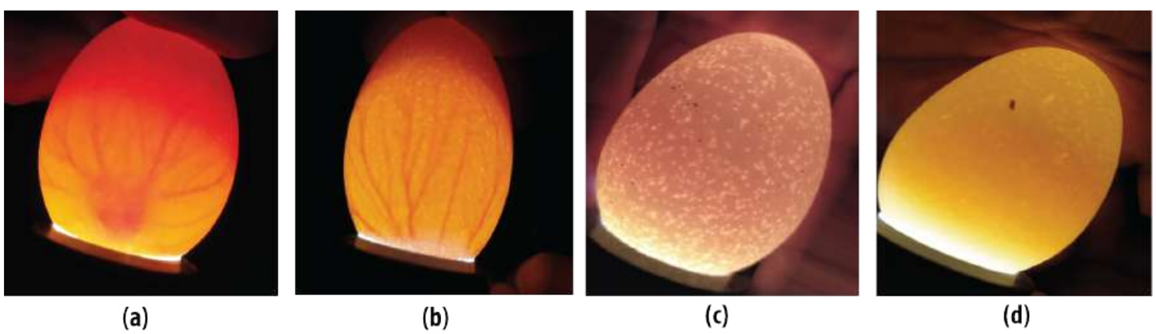

Figure 6: Sample images from the dataset: (a) Fertile, (b) Fertile, (c) Infertile, (d) Infertile

3.3.2. Reflection

Reflection, specifically vertical flipping, was applied to create additional variations of the egg images. This approach helps capture eggs in reversed positions or with altered appearances caused by reflections or other factors. By incorporating reflected images, the model learns to recognize fertility regardless of an egg's orientation.

3.3.3. Scaling

Scaling was used to adjust the size of segmented egg images, simulating variations in egg size. By increasing and decreasing the scaling factor, the model learns to adapt to eggs viewed from different distances and can determine egg fertility irrespective of size.

3.3.4. Translation

The egg images were randomly translated within a specified range, both horizontally and vertically. This spatial transformation introduces positional changes in the dataset, accounting for the possibility that eggs may not be perfectly centered during candling.

3.3.5. Flip

Horizontal flipping was applied to further enhance the dataset. This technique reduces location bias during candling, improving the model's robustness to egg position variations.

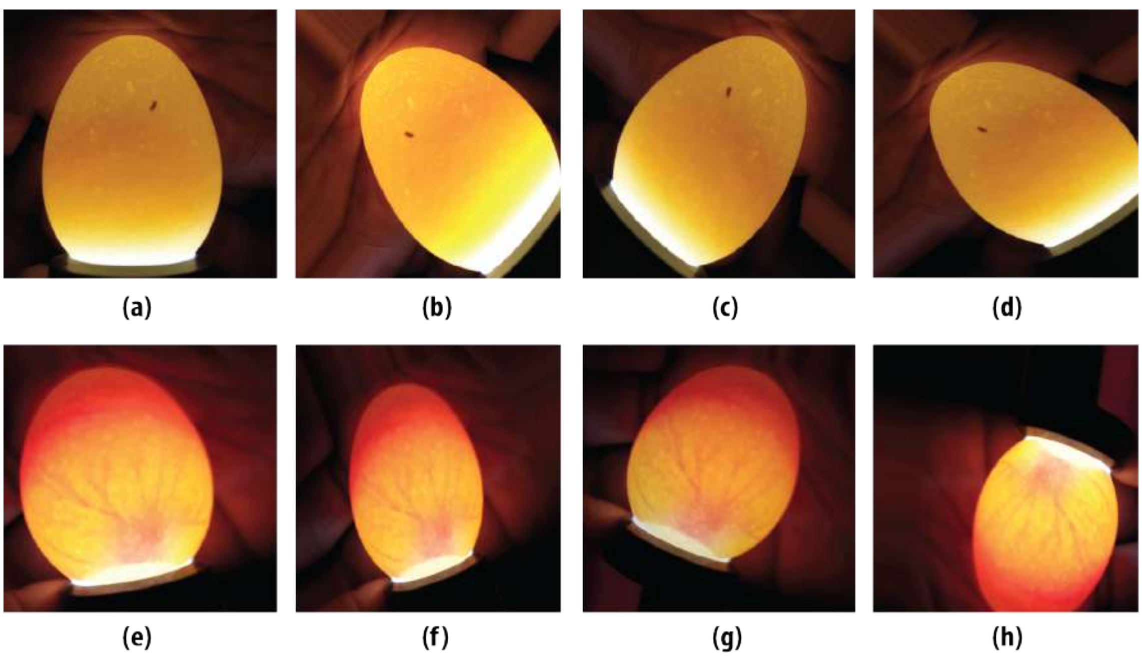

Figure 7: Sample images from the augmented dataset

Figure 7 presents examples of the augmented images, including both original and modified versions. The model was trained exclusively on these augmented images to improve generalization and performance. To mitigate overfitting, the initial (non-augmented) dataset was used during the testing phase.

3.4. Data Preprocessing

Image preprocessing enhances the quality of image data for classification tasks. To ensure the modelâs efficiency, the collected datasets must undergo preprocessing.

3.4.1. Image Resizing

Resizing images is a crucial preprocessing step in computer vision. Machine learning algorithms often perform better on images with reduced, consistent dimensions. Variations in the dimensions of newly acquired images pose challenges in building a standard machine learning model, so it is essential for all images in the dataset to have uniform dimensions in terms of size and depth. To achieve uniformity and optimize computational efficiency, all egg images are resized to 299x299 pixels.

3.4.2. Image Normalization

Image normalization helps improve model convergence during training and enhances generalization to new data. Normalization typically involves centering data around a zero mean and scaling input pixel values to a standard range [28]. For normalization, pixel values are divided by 255 to scale them between 0 and 1, facilitating effective learning.

3.4.3. Image Filtering

Data augmentation can sometimes result in distorted or poorly defined edges in images. Additionally, artifacts may appear within the images. To improve the quality and detail of augmented images, we apply a filtering technique. Specifically, a mild sharpening filter is used to enhance image clarity, emphasizing details by sharpening edges while reducing noise and distortions. This is achieved by enhancing high-frequency components, such as edges, while de-emphasizing low-frequency areas, such as smooth regions [29]. A mild sharpening filter is often implemented by subtracting a slightly blurred version of the image from the original. The equation for the mild sharpening filter is as follows:

$$S_{im}(x, y) = I_{im}(x, y) + (I_{im}(x, y) - B_{im}(x, y)) \times F \tag{1}$$

In this equation, $S_{im}(x, y)$ represents the sharpened image, $I_{im}(x, y)$ is the intensity value of the original image, and $B_{im}(x, y)$ is the intensity value of the blurred image at pixel location (x, y). The variable F is the sharpening factor, which controls the intensity of the sharpening effect. Figure 8 shows the results of applying the mild sharpening filter to the augmented images.

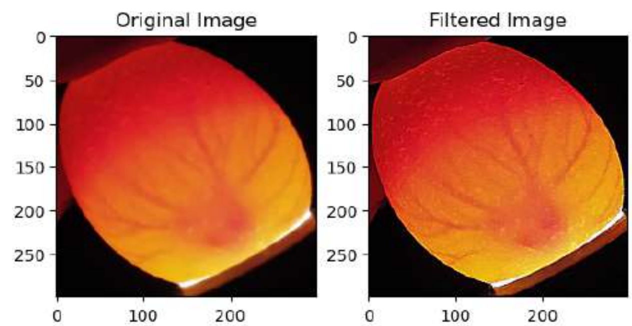

Figure 8: Effect of applying the filter on the dataset images

3.5. Proposed InceptionV3-EFD Model Architecture

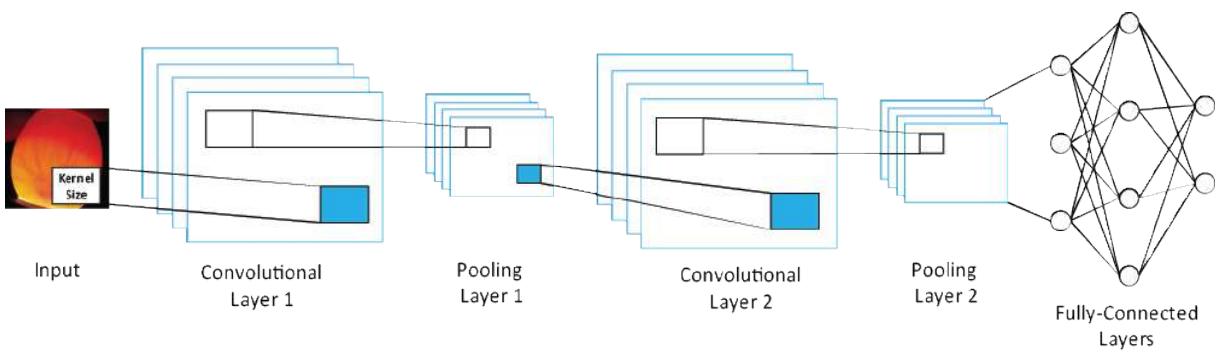

Figure 9: Traditional Convolutional Neural Network.

The Inception V3 Convolutional Neural Network (CNN) was developed by Google for image classification tasks. Szegedy et al. [30] introduced the third iteration of the Inception architecture in 2015, building upon the advances of previous models to enhance performance and efficiency in image classification. The Inception V3 architecture is both deep and complex, consisting of a series of interconnected inception modules. Each module contains

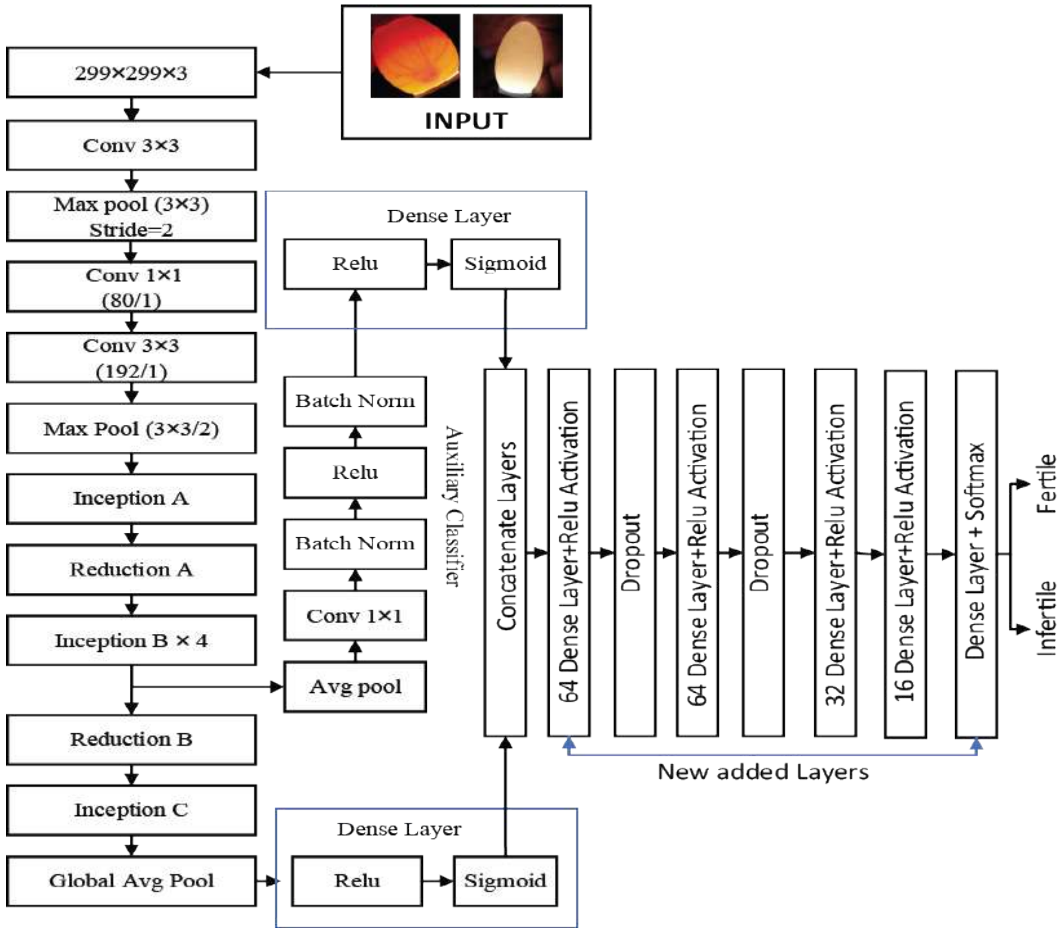

Figure 10: Proposed InceptionV3-EFD CNN model architecture.

multiple convolutional and pooling layers designed to extract unique features from the input image. Inception V3 employs factored convolutions, which reduce the number of parameters in the network without sacrificing accuracy. This technique enables the network to capture both local and global image features, thus improving model accuracy.

The Inception V3 architecture includes convolutional filters of sizes 1x1, 3x3, and 5x5, allowing the model to extract information at varying scales. The 1x1 filter reduces the complexity of the input, while the 3x3 and 5x5 filters capture intricate image details. Trained on the ImageNet dataset, which contains over 14 million images in 1,000 categories, Inception V3 is a pre-trained model that includes batch normalizationâa technique used to normalize inputs within the network. Batch normalization helps stabilize the training process and reduce the internal covariate shift, which is the change in the distribution of network inputs during training.

The InceptionV3-EFD model uses a traditional CNN architecture, which is well-suited for handling grid-like input data such as images, making it a strong choice for image classification tasks. When we view an image, our brains analyze extensive amounts of information; similarly, CNNs process input data through three main types of layers: convolutional, pooling, and fully connected layers, which work in tandem [31]. Additionally, a flatten layer is used to compress the input structure. Convolution itself is a linear operation, but to accommodate the nonlinear nature of image processing, CNNs introduce nonlinearity through activation functions immediately following the convolutional layers. ReLU and Softmax are key activation functions used in CNN development. Figure 9 illustrates the internal structure of a CNN.

Transfer learning is applied in our model to adapt the pre-trained InceptionV3 for the classification of fertile and infertile eggs. Transfer learning allows a pre-trained model to be fine-tuned for a new task, making it useful for image classification tasks with smaller datasets. It enables the model to improve prediction accuracy by leveraging knowledge from previous tasks [32].

In this research, transfer learning is used alongside the CNN model to categorize fertile and infertile eggs from the incubation system. Instead of using the original final layers of InceptionV3, new layers are added and fine-tuned to address the specific classification requirements of this task.

Figure 11 presents a detailed structural schematic of the modified InceptionV3-EFD model. Additional dense layers with dropout regularization have been incorporated into our model to enhance feature extraction and mitigate the risk of overfitting. By adding four dense layers with dropout, we struck a balance between model complexity and generalization capability. This design adjustment increased the model's ability to extract critical features and resulted in more accurate and reliable classification of egg fertility in real-time.

4. Results and Performance Analysis

The proposed model has been implemented in a real-time incubation system, and several experimental outcomes are described in this section for egg fertility detection and classification.

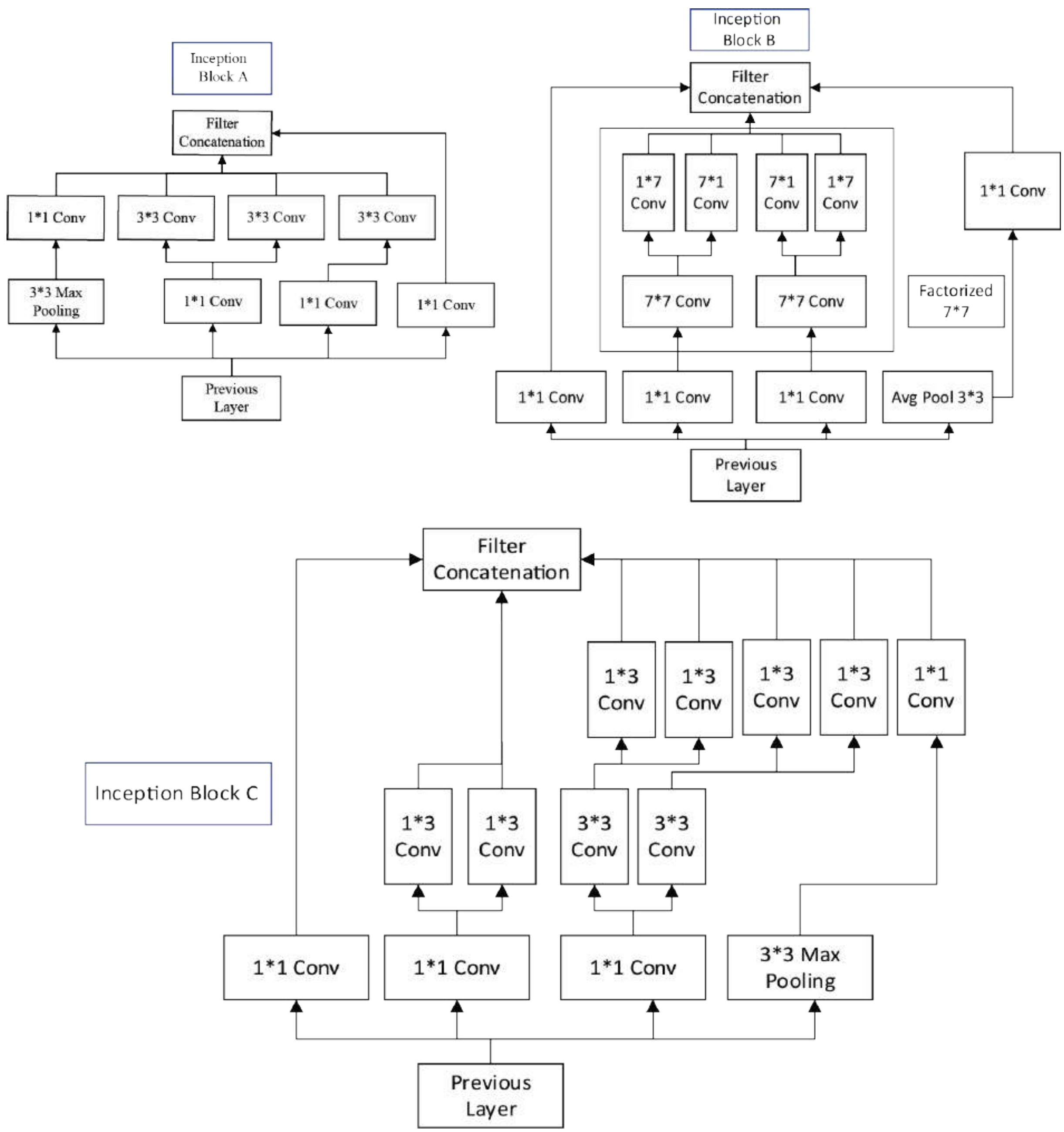

Figure 11: Detailed structure of the Inception blocks in the proposed InceptionV3-EFD CNN model.

4.1. Experimental Setup

A 64-bit Windows operating system with 8GB of RAM and an Intel (R) CoreTM i7-8700 CPU at 3.20GHz CPU has been used for a real-time experiment with the proposed system. An IoT-based egg incubation system is used to experiment with real-time egg fertility detection during the incubation period. The incubation system is modified and extended with camera sensors that take real-time pictures of eggs during the incubation period. The pretrained Inception-V3 model which had been trained using the Imagenet dataset obtained from the Keras, and subsequently fine-tuned. In the program's deployment, Tensorflow, KerasÂ and other similar frameworks have been used.

4.2. Hyperparameters

The prepared EFD_Data_Set is fed to the pre-trained IncpetionV3 model, and the weights of the model are modified by adding a few new dense layers. Finally, the newly developed InceptionV3-EFD model is trained with that data set. The proposed model is evaluated with several quantitative matrices and thereupon, fine tuning the hyper-parameters and configurations are settled down as per Table 2.

Table 2: List of the Hyper-Parameters that are used in the Proposed Model

Hyper-parameters	Values
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Epochs	50
Loss Function	SparseCategoricalCrossentropy
Activation	ReLU and Softmax
Image Size	299 x 299 x 3
Augmentation Techniques	Rotate, Scale, Flip, Zoom

4.3. Confusion Matrix

The confusion matrixÂ is a m*m matrix utilized for assessing the efficiency of classification models. The confusion matrix is a quantitative representation where the X-axis corresponds to the predicted values and the Y-axis corresponds to the actual values. The utilization of a confusion matrix in multi-class classification enables the computation of True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) values for each individual class [33]. These data can be used to compute the precision, recall, and F1-Score for each class. A confusion matrix can greatly help in visually estimating the performance of a model. The fertility of egg images considered in the current manuscript can be easily justified with the confusion matrix.Â Precision measures how many predicted positives are actually positive. It can be computed by class using the equation 2.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Recall determines the accuracy of properly predicting positive records. The equation 3 can be used to calculate it on a per-class basis.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

The F1 score is a measurement used to evaluate machine learning performance by combining precision and recall assessment. The F1 score is calculated as the harmonic mean of the precision and recall metrics of a model. F1 score is calculated by the equation 4

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

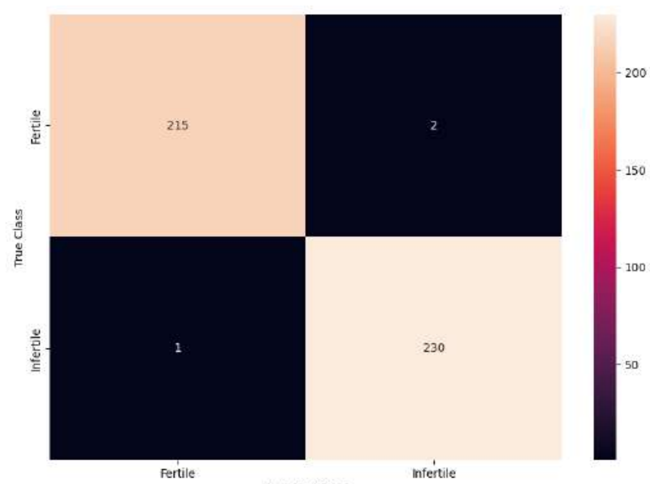

Figure 12: Confusion Matrix representation for the proposed model

The confusion matrix for the proposed model is shown in Fig. 12. From the confusion matrix, it is clearly observed that the models have been performing exceptionally well and classifying the fertile and infertile eggs for the incubation system effectively.

4.4. Classification Report

The precision, recall, f1-score, accuracy, and support for each class are all displayed in the classification report, a performance evaluation statistic. It is employed to evaluate how well the trained models perform with the test set. The procedure for determining the level of accuracy incorporates the division of the number of correct predictions by the total number of predictions obtained from the confusion matrix, as shown in the following equation 5.

$$Accuracy = \frac{TruePredictions}{NoofPredictions} \tag{5}$$

The classification report of the proposed InceptionV3-EFD model for egg fertility detection and classification is presented in Table 3. The classification report contains essential evaluation measures, including accuracy, precision, recall, and F1-score, for every class.

Table 3: Classification Report of the Proposed InceptionV3-EFD Model

Classification Reports				
Classifier	**Precision**	**Recall**	**F1-Score**	**Support**
Fertile	0.99	1.00	0.99	216
Infertile	1.00	0.99	0.99	232

The mean precision of the proposed model is 99.32%, which ensures its capacity to precisely predict all the positive cases across all the categories. The model exhibits a high level of proficiency in catching the majority of true positive cases, as evidenced by its average recall of 99.34%. The F1-score, a measure that combines precision and recall, has an average value of 99.33%. This value reflects the overall effectiveness of the model in achieving a balance between accuracy and recall. These results confirm the robust performance of the model in appropriately categorizing cases throughout the whole dataset.

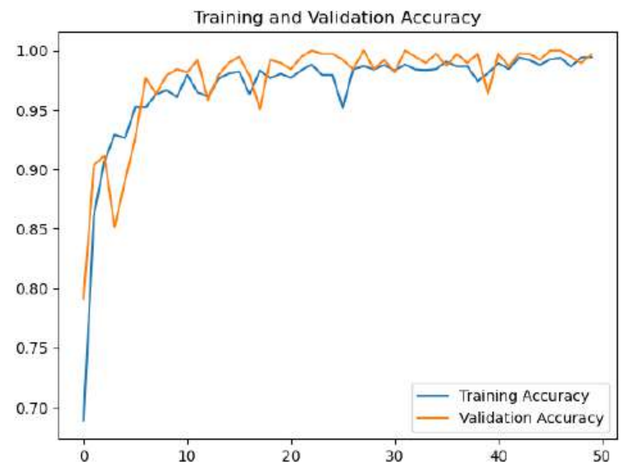

Figure 13: The learning curve for training and validation accuracy of the proposed model.

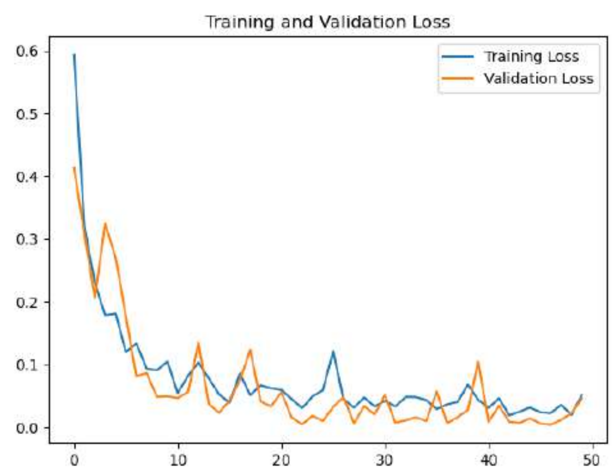

Figure 14: The learning curve for training and validation loss of the proposed model.

The model's learning curve in Fig. 13 and Fig. 14 exhibits rapid improvements in training and validation accuracy and a decrease in loss. This shows the model learning and generalizing successfully and indicates that the model is accurate at identifying egg fertility. The effectiveness of the proposed model and the classifier's ability to predict the fertility of an egg are clearly stated by the given ROC curve in Fig. 15.

An experiment is conducted in a real-time IoT-based egg incubation sys-

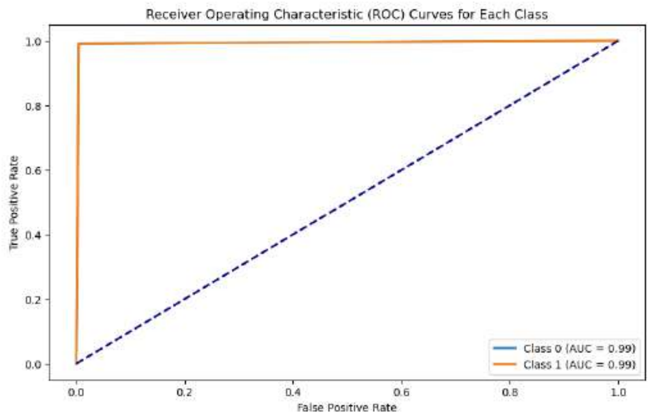

Figure 15: The ROC curve of the proposed model.

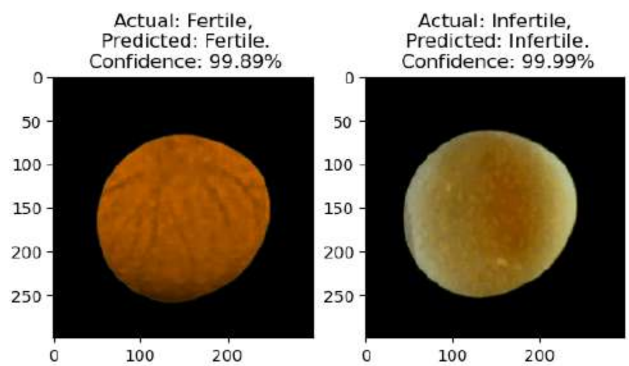

Figure 16: Real-time Egg Fertility Detection Results from the IoT-based Incubation System

tem to detect egg fertility using the proposed model. Real-time fertility detection of two samples from an IoT-based egg incubation system is shown in Fig. 16. It can be observed that the model clearly identifies egg fertility during the incubation period.Â

The proposed model is comparable to the other egg fertility detection and classification techniques as shown in Table 4. The testing accuracy of the proposed InceptionV3-EFD model is 99.33%. It is observed that our proposed model is better than that of the existing state-of-the-art systems.

Table 4: Comparison of the Proposed InceptionV3-EFD Model with other state of the art systems

Fertility Detection System	Accuracy
S Tolentino et. al., [11]	80.5%
Saifullah et. al., [12]	84.57%
Fadchar et. al., [13]	97%
Hashemzadeh et. al., [15]	98.25%
Saifullah et. al., [16]	98.2%
Proposed InceptionV3-EFD Model	99.33%

5. Conclusion

Egg candling is one of the most crucial and sensitive tasks during the incubation period. An automated egg fertility detection and classification system resolved the issues, enhanced the hatch rate of the eggs, and increased the productivity of healthy chicks. This research developed A CNN-based deep learning model named InceptionV3-EFD using transfer learning. Moreover, EFD_Data_Set has been created by taking real pictures of fertile and infertile eggs from different poultry firms during the incubation period, which ensured the precise and accurate classification of the proposed model. The system is trained and tested with the created data set and has achieved an outstanding test accuracy of 99.33% ensuring the reliable identification of egg fertility during incubation period.

CRediT authorship contribution statement

All authors developed the study concept and design. K. I. M., A. S., and M. R. J. collected the data. P. B., M. O. R., M. M. H., and M. R. H. performed data analysis. K. I. M., A. S., M. R. J., M. O. R. M. M. H. and M.

R. H. contributed to drafting and revising the manuscript. The final version of the manuscript is approved for submission by all authors.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper..

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Highlights

- Designed an IoT-enabled CNN model integrating InceptionV3 for egg fertility analysis.
- Enhanced InceptionV3 architecture with added layers, achieving 99.33% model accuracy.
- Created a dataset (EFD_Data_Set) with 4,021 images from 640 eggs during incubation.
- Achieved real-time classification with 99.32% precision, 99.34% recall, and 99.33% F1-score.
- System optimizes incubation by detecting infertile eggs, reducing embryo mortality.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.