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Classification of Cihateup duck egg fertility using convolutional neural network EfficientNet-B3

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ABSTRACT

Accurate detection of egg fertility is crucial to improve hatching success in duck farming. Conventional candling methods rely heavily on human expertise, making them subjective and error-prone. This study proposes an automated classification system for Cihateup duck egg fertility using candling images and a convolutional neural network (CNN) based on the EfficientNet-B3 architecture. Image enhancement techniques, including contrast limited adaptive histogram equalization (CLAHE), unsharp masking, and adaptive thresholding, were applied to improve image quality and feature visibility. The dataset consisted of fertile and infertile egg images captured at two incubation stages: the first 24 hours and the 8th–15th days. Data were split into training, validation, and testing sets with a ratio of 70:15:15. Experimental results show that image enhancement significantly improves classification performance. Without enhancement, the model achieved an accuracy of 49% with an area under curve (AUC) of 0.4226, indicating poor discrimination capability. With image enhancement, the proposed method achieved accuracies of 77% for the first 24 hours dataset and 80% for the 8th–15th days dataset, with AUC values of 0.9962 and 0.9317, respectively. These results demonstrate that EfficientNet-B3 combined with image enhancement provides an effective and computationally efficient solution for automated fertility detection of Cihateup duck eggs.

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1. INTRODUCTION

Indonesian local ducks including Cihateup breeds in West Java, Indonesia have contributed meat and egg to the household during the recent past [1]. The success of duck egg hatching heavily depends on the ability to distinguish between fertile and infertile eggs. Traditional methods, such as candling, are often inaccurate and require specialized skills based on the farmer’s experience, which can lead to errors in egg selection and affect production efficiency.

In previous research, chicken egg classification based on segmentation and fertility status has been carried out using a mask region-based convolutional neural network (Mask R-CNN) based approach to successfully detect, classify, and segment fertile and infertile eggs [2]. In another study, it highlighted the efficacy of hyperspectral imaging combined with machine learning as a potential green technology for egg fertility detection towards a sustainable egg industry [3]. Furthermore, research on detecting the fertility of chicken eggs using the extraction technique using first-order statistics (FOS) from image segmentation results classified with a backpropagation artificial neural network (ANN) produced relatively low accuracy, thus not achieving optimal results [4].

However, specific applications for Cihateup duck egg fertility have not yet been conducted, despite this species producing eggs with characteristics distinct from other poultry. This study opens opportunities to automate the process of classifying egg fertility based on candling images [5], [6]. For the classification of Cihateup duck egg fertility, the EfficientNet architecture will be selected to optimize model performance, aiming for higher accuracy with more computational efficiency, thereby producing a high-accuracy automated prototype.

2. METHOD

The candling method has long been used in the poultry industry to assess egg quality and fertility by observing their internal structure through lighting [7]. This assessment is conducted manually, making it prone to subjectivity and inconsistency, which has led to the development of automated approaches using image processing technology as a solution [8], [9]. In the experiments that have been carried out, it can be seen that contrast limited adaptive histogram equalization (CLAHE) can increase the local contrast of the image without increasing the noise so that it can improve the quality of the resulting image [10]–[12], while unsharp masking sharpens the edges so that details are clearer [13], [14], while adaptive thresholding converts grayscale images into binary adaptively so that they are effective in uneven lighting conditions so that they will improve the quality of the resulting image from the feature extraction process [15], [16].

Convolutional neural network (CNN) have become the standard for image classification tasks due to their ability to automatically and hierarchically extract features [17]–[19]. Various CNN architectures have been developed and applied across different domains. In 2019, researchers from Google AI introduced EfficientNet, a family of CNN models that optimizes performance using a compound scaling technique [20], [21]. This approach uniformly scales the network's depth, width, and resolution using a single scalar parameter, resulting in models that are more efficient and higher-performing compared to previous architectures. One variant of this family is EfficientNet-B3, which offers a balance between accuracy and computational efficiency [22].

The selection of EfficientNet-B3 as the CNN architecture for egg fertility classification is based on its superiority in achieving an optimal balance between accuracy and computational efficiency. While other architectures like ResNet and DenseNet offer high accuracy, EfficientNet-B3 surpasses them by yielding similar or even better prediction performance, yet achieved with a significantly lower number of parameters and computational requirements (giga floating-point operations per seconds (GFLOPs)). This advantage stems from the unique compound scaling method, which intelligently optimizes and balances the network depth, width, and input resolution simultaneously [23]. Consequently, EfficientNet-B3 provides a compact yet powerful model, making it ideal for the specific and sensitive image classification task of detecting egg fertility while also ensuring fast inference and practical implementation on resource-constrained hardware in real-world operational environments.

EfficientNet has been applied across various domains, and studies show that it can achieve high accuracy with better computational efficiency compared to previous models [24]–[26]. Integrating the candling method with CNNs using EfficientNet-B3 offers significant potential to improve both accuracy and efficiency [27], [28], particularly in classifying the fertility of Cihateup duck eggs. Figure 1 illustrates the research workflow conducted to classify egg fertility. The process begins with image acquisition of two egg classes (fertile and infertile), followed by splitting the dataset into training, validation, and testing sets. The preprocessing stage includes image enhancement (using CLAHE, unsharp masking, and adaptive threshold), building a TensorFlow data pipeline (involving resizing, normalization, batching, and prefetching), and applying data augmentation techniques such as flipping, rotation, and zooming to increase variability. Next, the images are processed using a CNN model based on EfficientNet-B3, which is trained and fine-tuned with callbacks such as ModelCheckpoint, EarlyStopping, and ReduceLROnPlateau. The model's performance is evaluated using a confusion matrix, receiver operating characteristic (ROC) curve, and area under the curve (AUC) to assess classification accuracy. Finally, the conclusion summarizes the effectiveness of the proposed method in automatically detecting fertile eggs.

In this study, two experiments will be conducted: the first for classifying egg fertility based on candling results with image enhancement and without image enhancement for fertile eggs at the first 24 hours, fertile eggs at the 8th and 15th days and infertile eggs using the EfficientNet-B3 CNN algorithm. Figure 2 is an example of a dataset: Figure 2(a) fertile eggs in the first 24 hours, Figure 2(b) fertile eggs at 8 and 15 days of age, and Figure 2(c) infertile eggs. This classification will use two classes, namely fertile and infertile, with the detailed quantities presented in Table 1. Next, the data is split with a ratio of 70% for training, 15% for testing, and 15% for validation, performed randomly. The details are presented in Table 2.

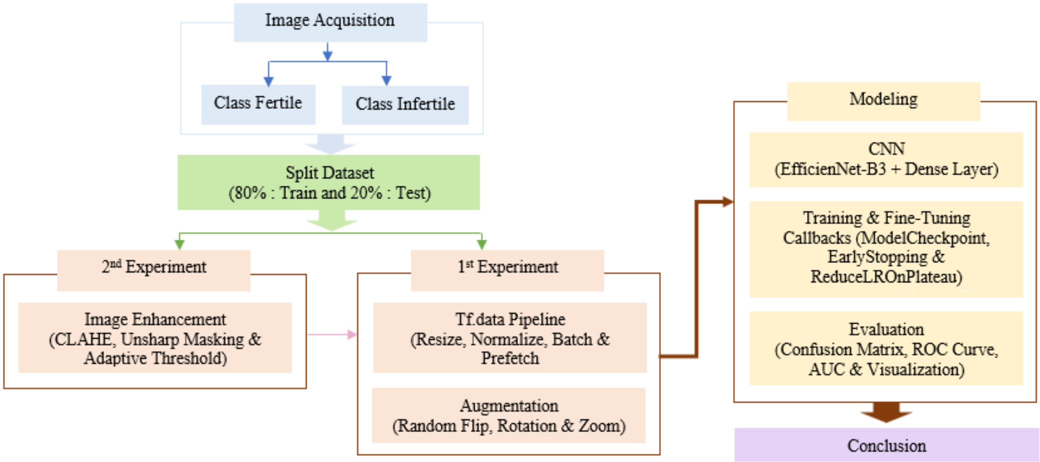
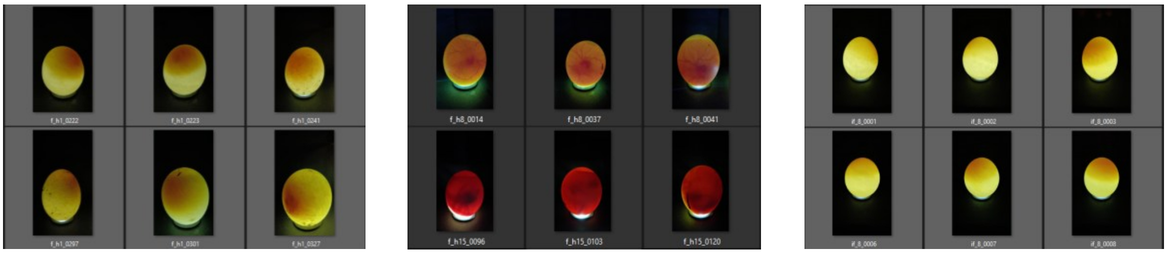


Figure 1. Experimental methods



(a) (b) (c)

Figure 2. Dataset of (a) fertile the first 24 hours, (b) the 8th and 15th days, and (c) infertile

Table 1. Dataset

No.	Experiment	Fertile	Infertile	Amount
1	The first 24 hours	867	849	1716
2	The 8th and 15th days	784	745	1529

Table 2. Data split

Data	The first 24 hours	The 8th and 15th days
Training	1200	1069
Validation	257	228
Testing	259	232

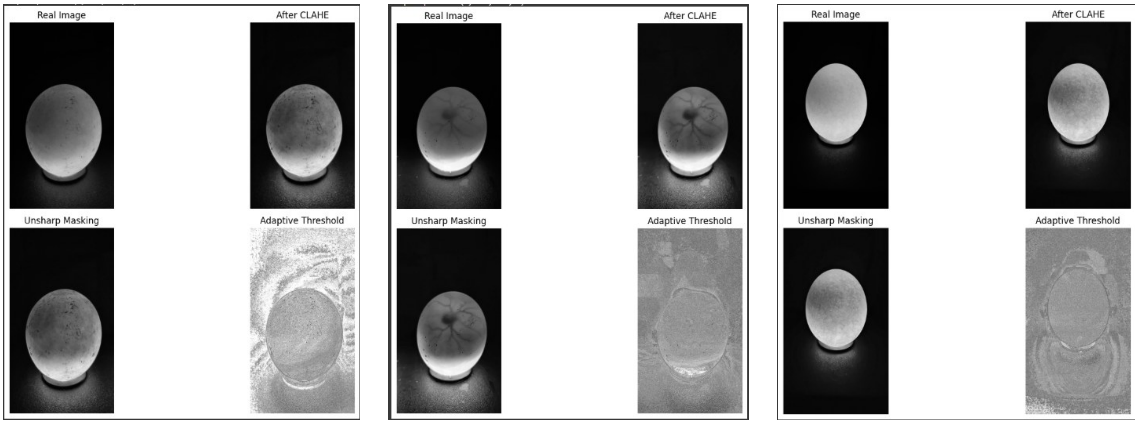
3. RESULTS AND DISCUSSION

3.1. Preprocessing

Figure 3 is the results of image enhancement applied to three egg samples: fertile at the first 24 hours as shown in Figure 3(a), fertile at the 8th and 15th days in Figure 3(b), and infertile in Figure 3(c) through three key processing methods: CLAHE, unsharp masking, and adaptive thresholding. CLAHE enhances local contrast, making fine structures on the surface of the egg and the embryo more visible. In Figure 3(b), the embryo and blood vessels are significantly more prominent compared to the unprocessed image. In samples Figures 3(a) and 3(c), shell surface patterns and the egg's contours are rendered with greater clarity. Unsharp masking technique sharpens edges by reducing blur effects. As a result, the egg's boundaries and texture details become crisper, facilitating distinction between internal and external areas. Across all samples, edge contrast is improved, simplifying the detection of embryonic features.

Adaptive threshold method converts grayscale images into binary ones by adapting to local lighting conditions. In Figure 3(a), the egg's shape is clearly defined, though embryonic details are less visible due to the dominance of noise. In Figure 3(b), the embryo's structure and interior regions of the egg are visualized, albeit with grainy noise. In Figure 3(c), the egg's contour stands out most prominently, while internal details remain relatively insignificant.

CLAHE was applied to improve local contrast and enhance embryo visibility without amplifying noise. Unsharp masking was used to sharpen edges and clarify structural boundaries, while adaptive thresholding was employed to handle uneven illumination by adaptively binarizing the images. Together, these techniques improve feature visibility and support more effective CNN feature extraction.

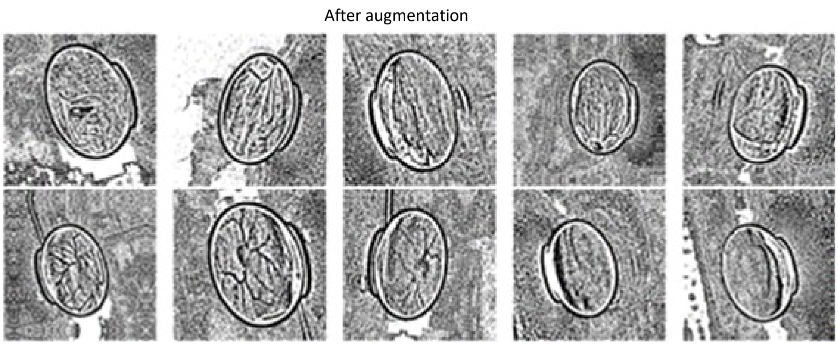


(a) (b) (c)

Figure 3. Image enhancement of (a) fertile at the first 24 hours, (b) fertile at the 8th and 15th days, and (c) infertile

3.2. Augmentation

Figure 4 shows the image after augmentation. Figure 4(a) displays the results of image augmentation with image enhancement applied to egg images using several transformations using augmentation techniques on Table 3 to enhanced egg images and their effects on model generalization. Figure 4(b) displays the results of image augmentation without image enhancement.



(a)

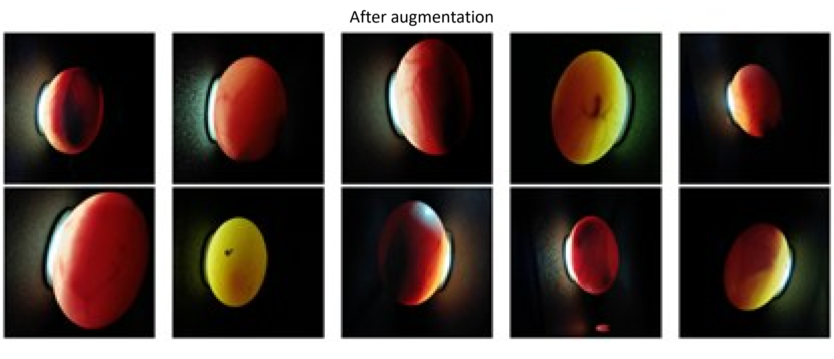


Figure 4. Image after augmentation of (a) with image enhancement and (b) without image enhancement

Table 3. Image augmentation techniques

Technique	Parameter	Purpose/impact on the model
Vertical flip	—	Helps the model learn orientation-invariant features
Horizontal flip	—	Improves robustness to horizontal orientation variations
Rotation	0.05 radians (≈ 2.9°)	Enhances model generalization to minor angular variations
Zoom	0.2 (+20%)	Enables the model to recognize relevant features across different scales and distances

3.3. Modeling

In the modeling pipeline for binary classification with EfficientNet-B3 as the backbone through transfer learning using parameter and fine-tuning configuration on Tables 4 and 5. The input resolution of 300×300 pixels were selected to match the optimal configuration of EfficientNet-B3, providing a balance between feature detail preservation and computational efficiency. This resolution is sufficient to capture critical candling features, such as embryo structures, while avoiding unnecessary computational overhead.

Table 4. EfficientNet-B3 model and training parameters

Parameter	Setting
Input image size	300×300×3
CNN architecture	EfficientNet-B3
Pretrained weights	ImageNet
Include top layer	False
Base model trainable (initial)	False
Pooling layer	Global average pooling
Dropout rate	0.3
Output layer	Dense (1 neuron, sigmoid)
Loss function	Binary cross-entropy
Optimizer	Adam
Learning rate (initial training)	3×10^{-4}
Batch size	16
Epochs (initial training)	15
Evaluation metric	Accuracy
Data augmentation	Flip, rotation, zoom
Callbacks	ModelCheckpoint, EarlyStopping, ReduceLROnPlateau

Table 5. Fine-tuning configuration

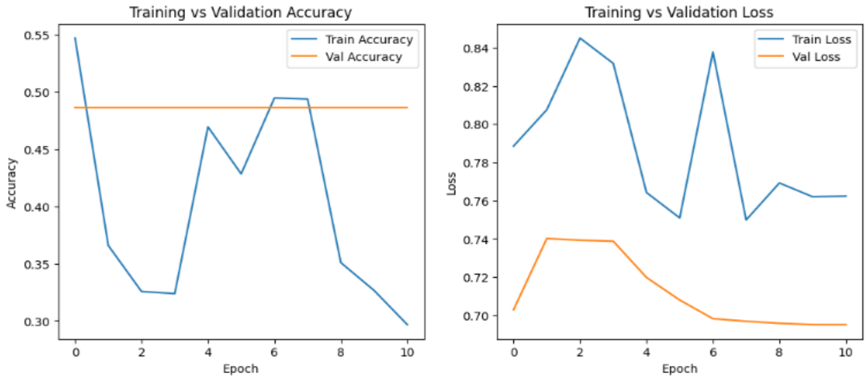
Parameter	Setting
Base model trainable	True
Trainable layers	Last 20 layers
Frozen layers	All layers except last 20
Optimizer	Adam
Learning rate (fine-tuning)	1×10^{-5}
Loss function	Binary cross-entropy
Evaluation metric	Accuracy
Epochs (fine-tuning)	5
Training data	train_ds
Validation data	val_ds
Callbacks	Same as initial training

Fifteen epochs were used for initial training to allow effective adaptation to the dataset without overfitting. Fine-tuning was limited to five epochs because the pretrained weights are already near optimal, and excessive fine-tuning may degrade previously learned representations. Only the last 20 layers were unfrozen during fine-tuning to adapt high-level, task-specific features while preserving low-level generic features learned from ImageNet. This strategy reduces overfitting and prevents catastrophic forgetting.

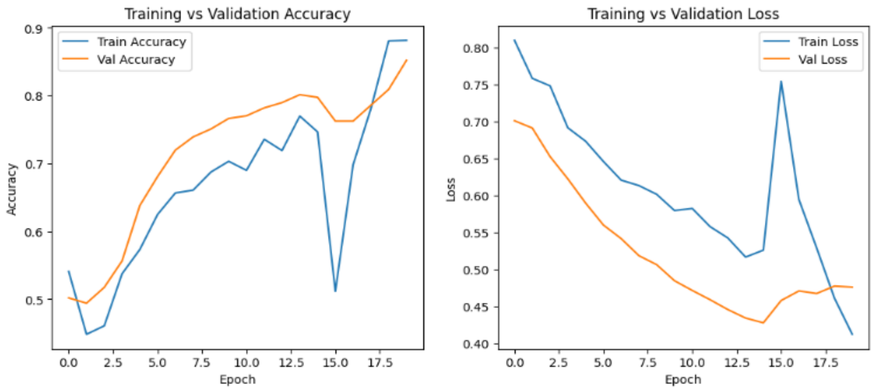
Figure 5 shows the training and validation graph. In Figure 5(a), the graph shows that training accuracy fluctuates sharply and decreases toward the final epochs, while validation accuracy remains stagnant at around 0.5, indicating that the model fails to learn effectively. On the other hand, training loss is unstable with sharp rises and drops, whereas validation loss is more stable and decreases gradually. This pattern suggests issues with convergence and model optimization, possibly caused by an unsuitable architecture, inappropriate learning rate, or data imbalance.

In Figure 5(b), the graphs show that both training and validation accuracy increase significantly until the final epoch, with validation reaching around 0.9. Training and validation loss also decrease consistently, although there is a brief spike at epoch 14. Overall, the model learns well, generalizes effectively on validation data, and shows only minor signs of instability.

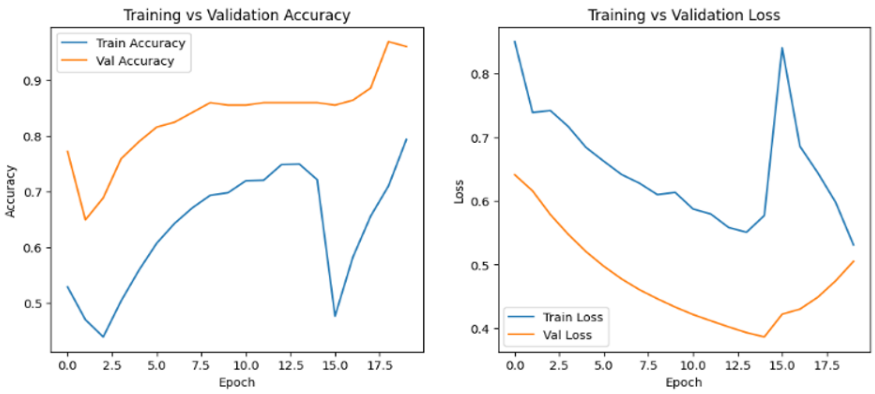
On the right Figure 5(c), the graphs show that training accuracy fluctuates sharply and even drops at certain points, while validation accuracy increases steadily, reaching close to 0.9. Training loss is also unstable with significant spikes, whereas validation loss decreases consistently. This indicates that the model generalizes well on validation data, although the training process remains somewhat unstable.



(a)



(b)



(c)

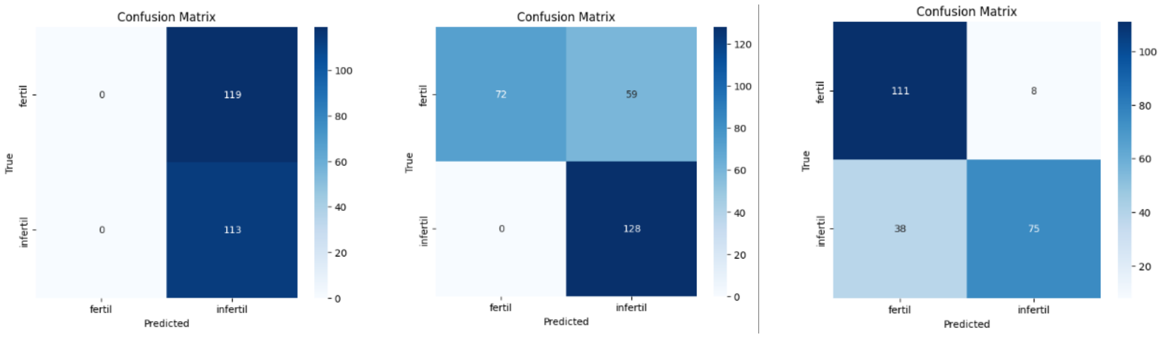
Figure 5. Training and validation graph (a) without image enhancement, (b) first 24 hours with image enhancement, and (c) the 8th and 15th days with image enhancement

3.4. Evaluation

Figure 6 shows the confusion matrix. In Figure 6(a), this confusion matrix shows that the model predicts all samples as infertile, causing all 119 fertile samples to be misclassified (0% recall), while all 113 infertile samples are correctly identified (100% recall), indicating a strong bias toward the infertile class and a complete failure to recognize fertile. The model's total failure (fertile recall 0%) is caused by extreme class imbalance, meaning the primary solutions lie in data balancing and loss function adjustment.

To ensure the model has sufficient samples from the minority class (fertile), Oversampling techniques such as synthetic minority over-sampling technique (SMOTE) must be applied to the training data. Subsequently, to prevent the model from ignoring the minority class, a weighted loss function or focal loss should be utilized. This approach inherently assigns a significantly higher loss weight when the model misclassifies a fertile sample, effectively forcing the model to pay greater attention to the minority class [23]. The success of these interventions must be measured using minority-class sensitive metrics, such as fertile class recall and F1-score, rather than just accuracy.

In Figure 6(b), this confusion matrix shows that out of 131 fertile samples, only 72 were correctly identified while 59 were misclassified as infertile, whereas all 128 infertile samples were classified correctly. The model performs very well in detecting infertile (100% recall) but is less effective for fertile (55% recall), resulting in unbalanced performance between the two classes. Figure 6(c) shows the results of the confusion matrix and classification report for the two-class classification model, namely fertile and infertile. From the confusion matrix, it can be observed that out of 119 fertile samples, 111 were correctly predicted (true positives), while 8 were misclassified as infertile (false negatives). Meanwhile, out of 113 infertile samples, 75 were correctly predicted (true negatives), and 38 were misclassified as fertile (false positives).



(a) (b) (c)

Figure 6. Confusion matrix of (a) without image enhancement, (b) the first 24 hours with image enhancement, and (c) the 8th and 15th days with image enhancement

The classification report shows on Table 6 that indicates that the model achieved 49% accuracy, correctly identifying all infertile samples but completely failing to detect the fertile class, showing strong bias and unbalanced performance. The classification report shows on Table 7 that indicates that the model achieves perfect precision but low recall for the fertile class, while for the infertile class it shows high recall but lower precision, resulting in an overall accuracy of 77% with better sensitivity toward infertile samples than fertile ones. Based on the classification report on Table 8, the model achieved good performance with 80% accuracy, showing high recall for the fertile class and high precision but lower recall for the infertile class, indicating the need to improve detection of missed infertile cases.

Table 6. Classification report without image enhancement

	Precision	Recall	F1-score	Support
Fertil	0.00	0.00	0.00	119
Infertile	0.49	1.00	0.66	113
Accuracy			0.49	232
Macro avg	0.24	0.50	0.33	232
Weight avg	0.24	0.49	0.32	232

Table 7. Classification reports the first 24 hours with image enhancement

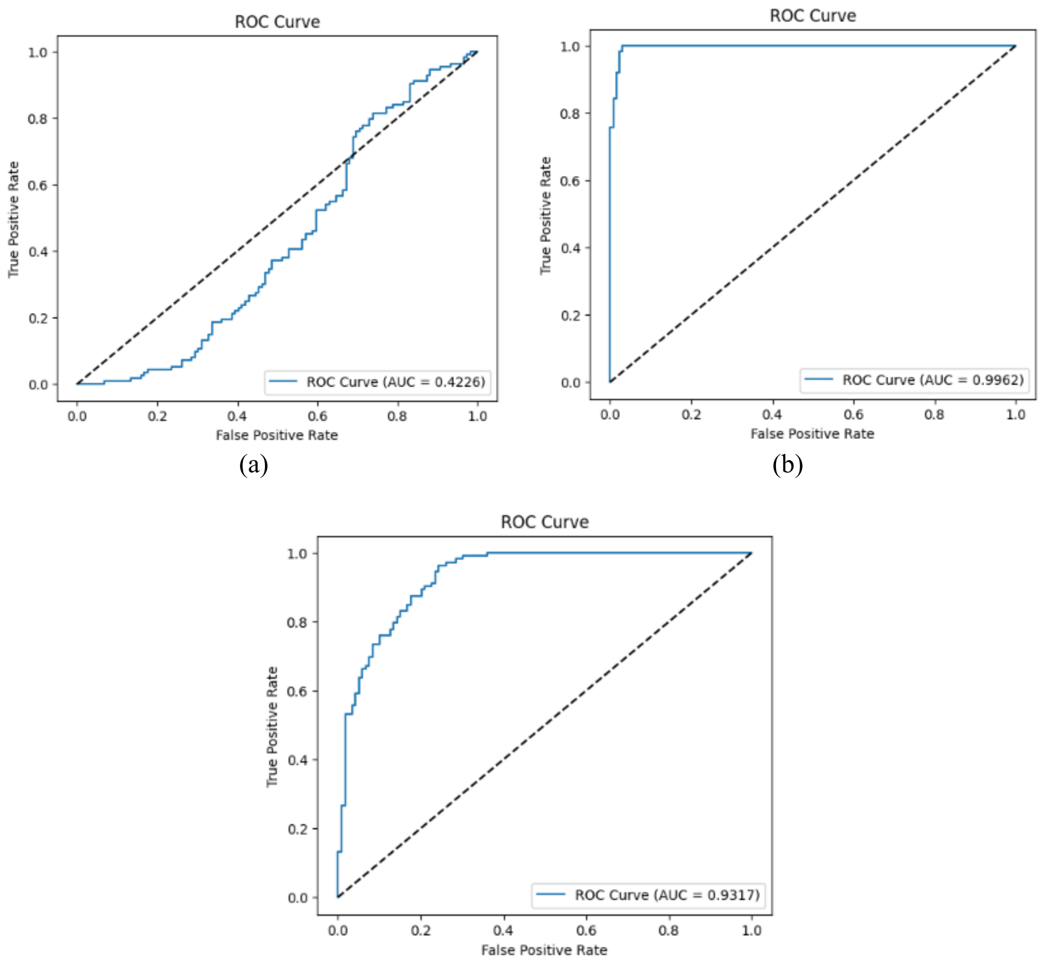
	Precision	Recall	F1-score	Support
Fertil	1.00	0.55	0.71	131
Infertile	0.68	1.00	0.81	128
Accuracy			0.77	259
Macro avg	0.84	0.77	0.76	259
Weight avg	0.84	0.77	0.76	259

Table 8. Classification reports the 8th and 15th days with image enhancement

	Precision	Recall	F1-score	Support
Fertil	0.74	0.93	0.83	119
Infertile	0.90	0.66	0.77	113
Accuracy			0.80	232
Macro avg	0.82	0.80	0.80	232
Weight avg	0.82	0.80	0.80	232

Figure 7 shows the AUC value in the ROC curve, in Figure 7(a) shows that ROC curve shows an AUC value of 0.4226, meaning the model performs worse than random guessing (AUC=0.5). This indicates that the model fails to properly distinguish between positive and negative classes, suggesting improvements are needed in the data, features, or model used. ROC curve in Figure 7(b) shows excellent model performance with an AUC=0.9962, which is very close to 1.0. The curve lies far above the diagonal line, indicating that the model has an almost perfect ability to distinguish between positive and negative classes. However, such a high value should be interpreted with caution, as it may suggest overfitting or evaluation on non-representative data. The AUC value in the ROC curve in Figure 7(c) is 0.9317, which indicates that the model has a 93.17% ability to distinguish between positive and negative classes. This means the model performs very well. The shape of the curve shows a high true positive rate (TPR) and a low false positive rate (FPR), indicating that the model has strong detection capability with minimal false positives.

For the visualization of the prediction results, see Figure 8. Figure 8(a) shows prediction visualization without image enhancement. Figure 8(b) shows prediction visualization the first 24 hours with image enhancement. Figure 8(c) shows the 8th and 15th days with image enhancement.



(a) (b) (c)

Figure 7. ROC curve of (a) without image enhancement, (b) the first 24 hours with image enhancement, and (c) the 8th and 15th days with image enhancement

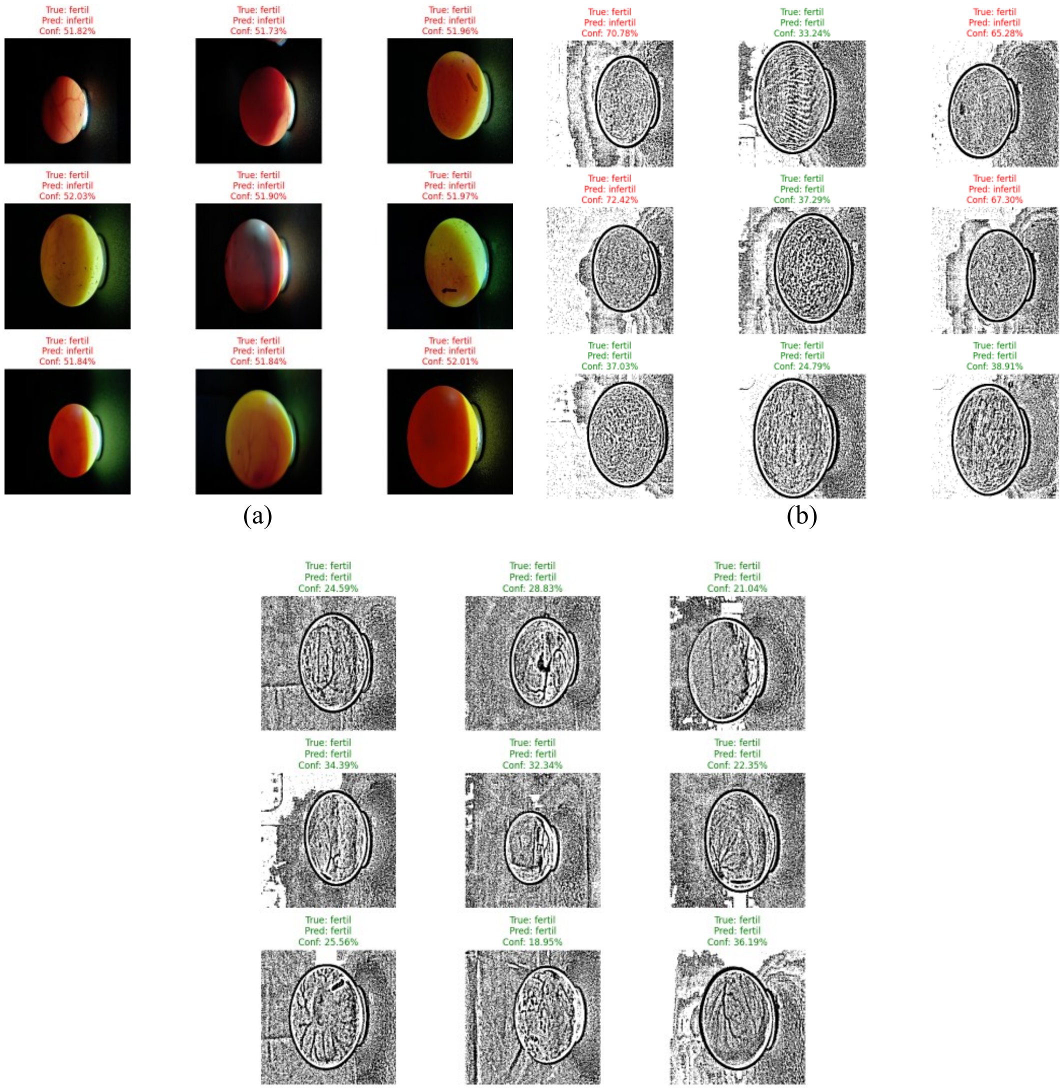


Figure 8. Prediction visualization of (a) without image enhancement, (b) the first 24 hours with image enhancement, and (c) the 8th and 15th days with image enhancement

4. CONCLUSION

The research results show that the application of image enhancement has a significant impact on model performance. Without image enhancement, the model failed to learn properly, as indicated by stagnant validation accuracy around 0.5, a low AUC value (0.4226), and a complete failure to recognize the fertile class. In contrast, with image enhancement applied to the first 24 hours of data as well as the 8th and 15th days, the model demonstrated much better generalization, achieving validation accuracy of up to 95%, high AUC values (0.9962 and 0.9317), and more balanced classification performance across classes, although some misclassifications still occurred. Overall, image enhancement improved training stability, accuracy, and the model's discriminative capability, although further optimization is required to minimize overfitting and improve class performance balance. Furthermore, these research findings can be extended with hyperparameter optimization techniques such as learning rate, batch size, and number of epochs to achieve more stable training. The application of regularization techniques such as dropout or weight decay is also important to reduce the risk of overfitting, while methods for handling data imbalance such as oversampling, undersampling, or cost-sensitive learning may help address class bias. In addition, the use of alternative model architectures such as ResNet, DenseNet, or vision transformer can be compared to obtain optimal performance. Experiments on larger and more diverse datasets are also required to ensure generalization, and the implementation of explainable artificial intelligence (XAI) approaches such as gradient-weighted class activation mapping (Grad-CAM) can assist in understanding the key features learned by the model.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to animal use has been complied with all the relevant national regulations and institutional policies for the care and use of animals.

DATA AVAILABILITY

The dataset that supports the findings of this study are available from the corresponding author, [EDSM], upon reasonable request.

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