Oocyte Microscopic Image Fertilization Prediction based on First Polar Body Morphology using YOLOv8

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Abstract— **The development of oocytes is crucial in the development and fertility of embryos in In Vitro Fertilization (IVF). There are several internal and external factors that could affect the fertilization competency of oocytes, one of which is the first polar body (PBI). However, there is still a debate regarding the influence of PBI on the developmental competency of oocytes. This work aims to find the correlation of the successful fertilization in which the mature oocyte develops into the stage of two pronuclei (2PN) by using the convolutional neural network (CNN) You Only Look Once (YOLO), which is widely applied to medical imaging problems. Our pipeline consists of exclusive segmentation CNN and classification CNN. First, light microscopic images of oocytes in the metaphase of meiosis II (MII) stage are captured, followed by the prediction of the likelihood of 2PN development after fertilization through intra-cytoplasmic sperm injection (ICSI). The image has its PBI segmented by the CNN and then cropped out of the original image. The PBI image is then fed into the prediction CNN to obtain the final result. The experiment showed that the best model is YOLOv8l-cls, trained on a dataset of 1006 images, with the top accuracy at 97.47% accuracy and 100.00% specificity. Furthermore, the ability of the model to predict without any additional features indicates the correlation between the PBI and the development tendency of oocytes.**

I. INTRODUCTION

Intracytoplasmic Sperm Injection (ICSI) is an essential process in In Vitro Fertilization (IVF) [1] involving the injection of a human sperm into the metaphase of meiosis II (MII) oocyte, developing into an embryo with varying qualities (see Fig. 1). A successful development of the fertilized egg can be observed in a day-1 (pronuclear stage) embryo image if it achieves the state of 2 pronuclei (2PN), with one from the sperm and one from the egg. Otherwise, it is considered abnormal, such as 0PN, 1PN, and >=3PN. To maximize the chance of successful fertilization, optimal embryo development, and therefore leading to pregnancy, a healthy MII oocyte is mandatory and is selectively acquired. Currently, the fertile oocyte is selected manually by embryologists based on its morphological appearance. There are several factors impacting the quality of an oocyte.

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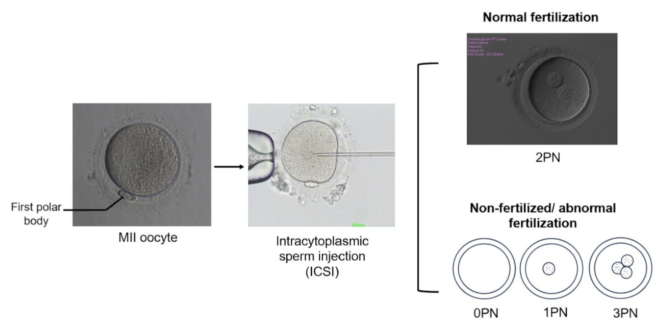

Fig. 1. Image of the phase of fertilization. Left is an image of MII oocyte with the first polar body (PBI). Middle is an image of the oocyte during fertilization by intra-cytoplasmic sperm injection (ICSI) technique. Right images depict possible outcomes after ICSI, including normal fertilization (2 pronuclei/2PN) and non-fertilized/abnormally fertilized embryos (e.g., 0PN, 1PN, >=3PN).

The patient's factors and the morphological appearances of oocytes including intracytoplasmic structures and extracytoplasmic structures, one of which is the first polar body (PBI) [2] [3]. PBI is a small cellular byproduct of the first meiotic division of an oocyte and remains within the zona pellucida. The importance of the quality of PBI in ICSI has long been studied and has been evaluated by scoring systems regarding Istanbul Consensus [4]. In general, an MII oocyte with healthy PBI is considered suitable for ICSI. This, relative to the grading system, considers PBI with the grade A or B [5]. Yet whether the impact of PBI quality influences the possibility of development into 2PN of oocytes is still controversial. Some work suggests that although the PBI impacts the quality of the oocyte, it has no direct impact on the success of ICSI [6] [7] [8] while the other suggests that the quality of PBI directly affects the ICSI failure rate [9].

Deep learning has been extensively applied in IVF recently. Convolutional Neural Network (CNN), in particular, has been utilized to a great extent in predicting the state of embryo development. Some CNNs have been experimented on and achieved promising results, including ResNet[10], Xception [11], EfficientNet [12], or the ensemble of several CNNs [13]. Deep learning has also been utilized on the segmentation of embryo/oocyte images. One particular work from Targosz et al. [14] has successfully segmented the components from the oocyte image and predicted its development with the accuracy of 95.70% by using DeepLabV3, a deep neural network model; though, the efficiency of the transformer relies heavily on the number of images, which could be the disadvantage in the developing countries as the amount of such microscopic images is relatively small. In our previous work [12], the accuracy of transformers is inferior to that of CNNs when trained on relatively small datasets (1099 images) of embryo images. Though, little work has been done on using CNNs on the oocyte segmentation problem. The usage of CNNs in the segmentation of medical images, however, is widespread. One particular network, You Only Look Once (YOLO) [15], is a regional proposal CNN that is characterized by its speed and accuracy.

YOLO saw a lot of applications in medical imaging on several domains [16]. This work accesses the influences the PBI morphology has over the possibility of a successful fertilization of the oocyte by using a YOLO CNN model to segment the PBI from the oocyte microscopic image in the stage of MII, predict whether it is developed into the stage of 2PN, and find correlations of the result to the PBI grading score. This work, to the best of our knowledge, is among the first to utilize CNN in predicting ICSI outcomes. This work also explores the possibility of using deep learning on the relatively small dataset of microscopic images which could be an issue in the developing country.

This paper is organized as follows: Section II describes the dataset and data augmentation. Section III explains the model. Section IV discusses the results while section V summarizes the key findings and ongoing efforts.

II. MATERIALS AND METHODS

A. Dataset Generation and Characteristics

Light microscopic images of oocytes in the state of MII are provided by the Division of Reproductive Medicine, King Chulalongkorn Memorial Hospital. There were 1006 images in total. After ICSI, 860 oocytes were fertilized resulting in the 2PN stage embryos and were classified as 2PN, whereas 146 oocytes were not fertilized or abnormally fertilized and were classified as non-2PN (e.g., 0PN, 1PN, >=3PN). Among these images, 782 oocytes received a PBI score of A, 677 of which are 2PN and 105 are non-2PN. The B grade consists of 224 images, of which are 183 2PN, and 41 non-2PN. Figure 2 illustrates the distribution of oocytes by fertilization outcome and quality grade. The age range of patients in this dataset spans from 25 to 50 years. This study was approved by the Institutional Review Board, Faculty of Medicine, Chulalongkorn University (IRB No. 764/64).

B. Balancing and Augmentation of the Dataset

The 1006 images in total are raw data and imbalanced, with 860 images corresponding to 2PN and 146 images to non-2PN. To address the imbalance, horizontal flipping and duplication were applied to the non-2PN images, resulting in an augmented set of 584 images. The 2PN images were randomly selected to match the augmented non-2PN set, yielding a final dataset of 1168 images with a balanced

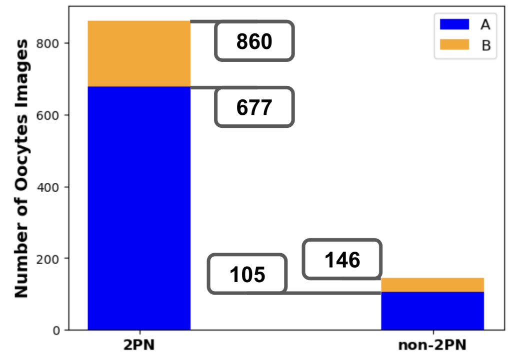

Fig. 2. Stacked bar chart of distribution of oocytes by fertilization outcome and quality grade

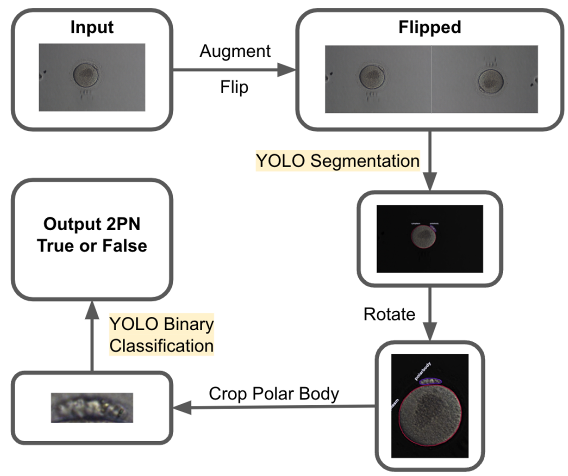

Fig. 3. The experimental pipeline of the segmentation and classification process. The classification CNNs tested include YOLOv8s-cls, YOLOv8m-cls, and YOLOv8l-cls.

50:50 ratio between 2PN and non-2PN data. The dataset of 1168 images was split into a ratio of 70:10:20, 816 images for training, 115 images for validation, and 237 images for testing. This allocation, dedicating 70% of the dataset to training, strikes a good balance between exposing the model to a variety of images, which is essential for learning patterns and features effectively, and providing a sufficient number of samples for validation and testing to ensure the model's robustness against unseen data.

C. Image Processing Pipeline

The images are augmented by vertical flipping to increase the amount of data and allow the model to observe several positions of the PBI. Figure 3 shows the overall pipeline of our experiment. The YOLOv8 segmentation model is applied to segment the PBI and locate its position. The image is then rotated to move the PBI to the top and the PBI is cropped based on its position. Lastly, the cropped PBI image is used to predict the development by using the YOLOv8 Classify model. Before the classification, the PBI image with non-2PN ground truth is augmented by flipping to add more images to the dataset and counteract the class imbalance.

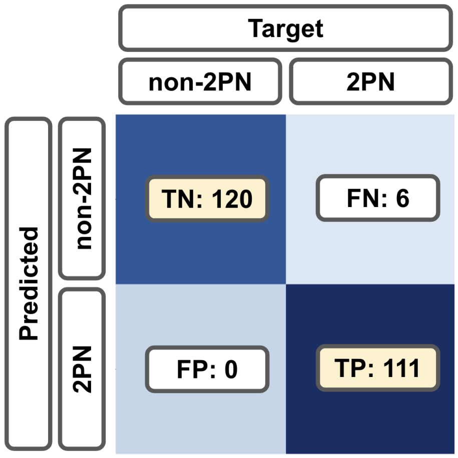

Fig. 4. Confusion matrix of the YOLOv8l-cls model predicted on test images.

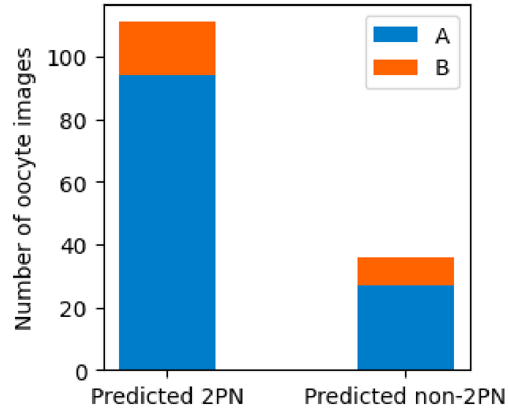

Fig. 5. Stacked bar chart of the PBI grading score distribution on the prediction of YOLOv8l-cls on the test set.

D. Model Selection

YOLOv8 Classify has been selected as a primary model structure. Given that YOLO offers several pre-trained models, this study compares the performance of YOLOv8 Classify Small, Medium, and Large.

E. Evaluation Metrics

The accuracy, sensitivity, and specificity of the classification model are measured. Sensitivity is used to measure the model performance on the 2PN classification and specificity is used to evaluate the model performance on the non-2PN classification.

III. RESULTS

Table I shows the performance of each model. The YOLOv8l-cls model achieves the highest accuracy at 97.47%, specificity at 100.00%, and sensitivity at 94.87%. The confusion matrix for the YOLOv8l-cls model, predicted on the test images, is presented in Figure 4, with true negatives (TN) equal to 120, false negatives (FN) equal to 6, false positives (FP) equal to 0, and true positives (TP) equal to 111. It is apparent that the model is more effective in predicting the negative class, non-2PN, as indicated by a higher specificity compared to sensitivity.

TABLE I. The performance of the models using only test images as inputs and BCE loss.

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)
YOLOv8s-cls	88.19	93.16	83.33
YOLOv8m-cls	89.87	88.03	91.67
YOLOv8l-cls	**97.47**	**94.87**	**100.00**

IV. DISCUSSION

Figure 5 shows the distribution of PBI grading scores by the predictions with YOLOv8l-cls. It is observed that the model is likely to predict 2PN with the grade-B PBI. Given that 20% of PBI in the datasets are scored as B, it could be concluded that our model prioritizes the grade B in positive prediction.

The results are reasonably aligned with the dataset, as there are more images with a positive 2PN ground truth. Since the model can accurately predict development based solely on the image of the PBI, without considering any other factors, it serves as evidence of the impact of PBI on the successful fertilization of MII oocyte. However, the model could be further developed in several ways. For instance, experiments could be conducted to select a more robust segmentation CNN. The cropped PBI image could be further processed to ensure that the model makes predictions based on the features of PBI only. In addition, various other factors, including cytoplasmic features, extracytoplasmic factors, or patient information such as age, underlying conditions, and semen quality, could be integrated to enhance the model's predictive efficiency. Moreover, more parameters could be computed from the physical features of PBI such as the area ratio or pseudo score similar to that given by embryologists.

There are also some limitations of the model. First, the model does not include the information of sperm quality, which also essentially contributes to the fertilization process. The model's interpretation of the PBI score, though apparent, remains inconclusive. Therefore, additional experiments focusing on a dataset with a balanced PBI grading score are recommended. Additionally, 2PN stage prediction is just the initial and surrogate outcome in IVF treatment. Blastocyst formation rate and/or pregnancy outcomes will be the outcomes required in further study.

In reflecting our work, we acknowledge an oversight which is the absence of the embryologist's input in predicting whether an oocyte would develop into 2PN or non-2PN stage. The data would have allowed for a benchmark between the model accuracy and the real-world application.

V. CONCLUSIONS

This work explored the effect of PBI physical quality in the possibility of the successful fertilization and development of oocytes into 2PN by utilizing CNN segmentation and prediction pipeline. The model takes light microscopic images of oocytes at the MII stage and predicts if the oocyte will achieve 2PN. The most successful model is YOLOv8l-cls with 97.47% accuracy, 100.00% specificity, and 94.87% sensitivity. We also present a method to utilize the small imbalance oocyte images dataset by in-augmentation balancing. Future studies could be done on integrating additional factors such as patient ages, patient characteristics, other intracytoplasmic and extracytoplasmic features of oocyte and male factors to improve model performance.

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