Viability Assessment of Bull Sperms Using Deep Learning

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***Abstract*—Quality assessment of bull sperms is a necessary task to process to increase a fertilization rate when applying methods of Assisted Reproductive Technology including In Vitro Fertilization and Intracytoplasmic Sperm Injection. Presently, the development of Computer-Assisted Sperm Analysis (CASA) allows scientists to assess the quality of bull sperms automatically in some processes such as sperm motility. However, scientists commonly perform the viability assessment process manually that surely requires many endeavors and highly time-consuming. In addition, the standard commercial CASAs provide only a module for assessing sperm motility. Unfortunately, to add an extra module of the assessment of sperm viability to the standard CASA is much costly. In this study, we proposed a novel sperm detection and viability classification system that use to distinguish dead or alive cell of the bull sperms by using Faster Region-based Convolutional Neural Networks (Faster RCNN). The performance of the proposed system was evaluated in term of sperm detection and viability classification. The results of the performance evaluation process revealed that it provided a high accuracy for sperm detection (90.72%) as well as the viability classification (84.49%). Based on these results, it clarified that our proposed system had a great potential to use in the real-world scenarios.**

***Index Terms*—sperm detection, viability classification, deep learning, faster RCNN**

I. Introduction

The number of populations is rapidly growing. This also leads to an increasing demand for food globally. In beef production and dairy farming industry, natural reproductive is not an appropriate way as it has limitation to produce a high quantity of beef and milk. In addition, the farmers often face the problem of infertility or low fertilization rate. Presently, Assisted Reproductive Technology (ART), such as In Vitro Fertilization (IVF) [1] and Intracytoplasmic Sperm Injection (ICSI) [2] have been developed in order to increase the quality and quantity of beef and milk production. It can be used to solve the problem of infertility in humans and animals caused by the abnormality and deficiency of sperms. Moreover, the ART techniques have been used to shorten the generational interval and propagate valuable genetic stock from breeding populations and reproductive research [3]. However, the sperms that were selected to be used in ICSI and IVF should be the high-quality one. The quality of sperm can be measured in terms of motility, viability, and abnormality. In the last few decades, Computer-Assisted Sperm Analysis (CASA) has been developed to be used as a tool for a sperm quality measurement. Most commercial CASA consist of modules that can be effectively measured the sperm motility. However, adding the modules for measuring the sperm viability and abnormality are very costly. Especially, for viability measurement module, it cannot automatically classify and count the dead or alive cells. This means the technicians have to classify and count the dead and alive cells manually. This process requires an endeavor and time-consuming.

In the present, deep learning plays an important role in bioinformatics and biomedical. With the availability of various deep learning algorithms, many difficult biological problems were been solved [4]. The deep learning is a family of artificial intelligence and machine learning methods based on learning data representations. It has been applied to many different fields such as bioinformatics [4], computer vision [5], medical image analysis [6], and etc. Information processing and communication patterns, for example, recurrent convolutional neural networks [7] and Convolution Neural Networks (CNN) [8] have inspired most algorithms of deep learning.

In the field of bioinformatics, object detection and classification, which is a part of the deep learning, have been utilized substantially together with biological experiments in laboratories. During the past decades, there were several previous studies related to the object detection and classification. Shaoqing Ren *et al.* [9] presented a state-of-the-art object detection networks depend on Region Proposal Algorithms (RPN) to hypothesize object locations. They used RPN to predict object bounds and scored at each position as well as detected objects by utilizing Fast Region-based

Manuscript received May 20, 2020; revised November 16, 2020.

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doi: 10.12720/jait.12.1.71-77

Convolutional Neural Networks (RCNN). Omar Javed and Mubarak Shah [10] proposed a method to track and classify objects in realistic scenarios on an automated outdoor surveillance system. The system detected a recurrent motion for each tracked object by using a new feature vector called a Recurrent Motion Image (RMI) for computing iterative the motion of the objects. A yield of RMI was certainly dissimilar for each different type of an object.

Figure 1. Example of an image performed image processing techniques; a) an original image, b) an image with nosing, c) an image with smoothing, and d) a color-contrast image

A popular input data applied in the area of deep learning is a collection of images or photos containing an interested object. However, the image itself surely contains among the interest objects, image background, and image noise. The image background is a Region of Uninterest (ROU) that should be omitted or ignored after a process of data preprocessing. The image noise is a random variation of brightness in images presenting as an aspect of electronic noise. With an intelligence of deep learning algorithms, it is possible to distinguish the interest objects apart from ROU; however, this does not include the image noise (Fig. 1b). The image noise should exclude from the input image data due to improving performance. Fig. 1 demonstrates image examples performed several techniques of image processing that typically uses for data preparation. For example, ref. [11] presented a novel method to mitigate low-level vision problems by combining sparse coding and deep networks pre-trained with denoising auto-encoder. They tested the proposed method in unsupervised feature learning. To compare to traditional methods, the effectiveness of their system had been clearly demonstrated in experimental results. This example insists that the data preprocessing process is important task for any systems significantly. Moreover, other image processing techniques have been used for preparing the data, such as denoising, image smoothing (Fig. 1c), edge sharpen and image color contrast (Fig. 1d). The image smoothing is a technique to denoise the image. The color contrasting is a technique to emphasize the image color and brightness; then, an interested object should be dominant. Y. Ireaneus *et al.* [12] introduced a tumor classification in Mammogram breast cancer images. Two problems had been addressed in their study; first, a problem to detect tumors as suspicious regions that found in a very weak contrast object compared to their background; second, a way to extract features which classified tumors. As the first problem, they enhanced the image contrast by using a contrast stretching technique. The performance of their classifier, i.e., Support Vector Machines (SVM), was effective because the input images had been adjusted and suitable for their system.

For a sperm classification, several related studies had been reported. Michael Biehl *et al.* [13] applied Learning Vector Quantization (LVQ) in automated boar semen quality assessment. Their system classified the sperms into normal and non-normal sperms based on grey-scale images. Serge Zaugg *et al.* [14] introduced four modules of automated real-time classification of clicks from sperm whales and impulsive sounds produced by ships. Two modules detected segments containing the impulsive sounds within a specific frequency band and returned the impulses' positions. The rest modules classified the detected impulses as sperm whale clicks or ship impulses.

In this study, we used a deep learning algorithm to minimize the problem of bull sperm detection and classification as mentioned above. This system was processed automatically to distinguish between dead and alive cells based on input images features such as color apparent to the head of the sperms. The data preprocessing process was also a part of this system. We used various techniques, e.g., denoising, image smoothing, edge sharpen, as well as color and brightness contrast sketching. Generally, scientists assess the quality of bull semen in term of viability manually that was a time-consuming process; then, this system attempted to address this difficulty. An objective of the study was to develop an automatic system for the bull sperm classification with potential results. We expected that this system should provide satisfying results similar or better when comparing to a manual process.

The remainder of the paper is organized into six sections as follows: Section II introduces the system process. Section III describes the results and discussion. Section IV discusses the obtained results and findings. Section V presents a conclusion.

II. The Proposed Method

In this study, we implemented the system of sperm detection and classification using TensorFlow [15] based on a Graphics Processing Unit (GPU). This system followed instructions published in [16] and [17]. We attempted to use the system along with our own dataset, i.e., an image collection of the bull sperms. This collection had been gathered manually by capturing images from a glass slide. To generate a training dataset, the images were labeled as dead or alive sperms distinguished based on the color on the head of the sperms. The white color is classified as alive; whereas the red color is set as dead. Fig. 2 demonstrates to the example of the raw image data. This figure should be processed in the preprocessing step prior processing through the detection and classification system. As we observed, the objects were concordant to the image background.

To prepare the input data, we applied several techniques in image processing to clean and refine the images. For implementation, we used Open source Computer Vision (OpenCV) as a system library. OpenCV [18] is an open source library programming function. It aims at real-time computer vision.

Several preprocessing techniques had been performed.

1) Denoising
2) Image smoothing
3) Edge sharpens
4) Color and brightness contrast sketching

These following techniques are necessary to prepare the data because, in fact, the result performance provided from the model depending on the quality of the input images to the system. Fig. 3 presents an example of the preprocessed image. The dominant object in the image had been intensively focused due to the techniques of our proposed steps. Their edges were clear and distinguishable from the background.

Figure 2. Example of a raw image

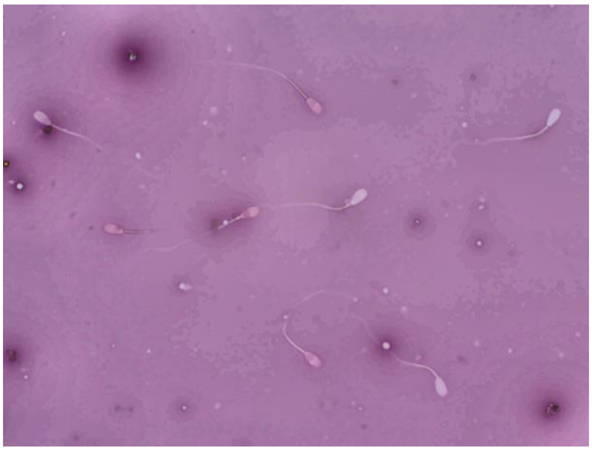

Figure 3. Example of an input image after our preprocessing process

Tensorflow provides several pre-trained object detection classifiers in its model zoo [19]. For this system, we used the pre-trained classifier on COCO dataset, called the Faster-RCNN-Inception-V2 model.

As presented in [19], Google provided some comparative results between different object detection models. The Faster-RCNN-Inception-V2 model consumed the speed 58 milliseconds with reasonable average precision, i.e., 28. The outputs of this model presented as boxes marking the detected objects. To compare between Single Shot Multibox Detector (SSD) and Faster RCNN, the SSD was faster than the Faster RCNN but has lower average precisions. Thus, the SDD might be suitable to use on a low computational device, e.g., a mobile device, rather than in a personal computer. For the other models, they were much slower than the Faster RCNN significantly. Therefore, the Faster RCNN was chosen to use in this study due to reasonable advantages, i.e., fast and high precision.

Here, we introduced the main aspect of the Faster-RCNN-Inception-V2 model. It had been developed based on Region-based Convolutional Neural Networks (RCNN) and Fast RCNN. The RCNN was intuitive but very slow; while the speed of Fast RCNN was improved, but the selective search algorithm to generate regions was a major bottleneck. The Faster RCNN had been proposed for omitting these remained problems. It consisted of steps briefly described as follows:

1) Input images were scanned into the algorithm
2) The Convolutional Neural Networks (CNN) performed feature extraction over the entire images at once.
3) The extracted image features processed to the region proposal network (RPN). There were a few steps of the RPN. First, the input of the RPN came from the last layer of the initial CNN that a 3x3 window shifted on the feature map and then mapped it to a lower dimension. Second, at the location of each sliding window, several possible regions based on k fixed-ratio anchor boxes, e.g., tall boxes and wide boxes, should be generated. Finally, in each detected regions (ROI), the object was scored, and the bounding box should be assigned.
4) The output of the previous step fed to a softmax layer that extended the neural network. Note that results from the softmax layer represented as the class probability of each bounding box. Moreover, a linear regression was utilized to tighten the bounding box of the existed object.

Note that Step 1 to 3 present in Fig. 4. Subsequently, the Faster-RCNN-Inception-V2 model can be performed both detection and classification. It used CNN to extract the image features and used RPN to detect the objects. Then, it applied the neural network to classify the detected objects.

This system had been used to the sperm image data as presented in Fig. 3. The dataset consisted of approximately 1,000 microscopic images of sperms that were stained with viability staining and fixed on the glass slide [20]. The pictures were captured using a compound microscope at 40X. For each image, the sperms colored in red are classified as dead cells, while the white head sperms are classified as alive cells. Fig. 5 demonstrates a user interface of the sperm classification system and a window resulting in the viability of the sperms. The system detected the sperms showing on the images as well as distinguished them into dead and alive sperms. Moreover, a statistical data report was presented, i.e., how many sperms existed in the image and how many sperms were alive or dead.

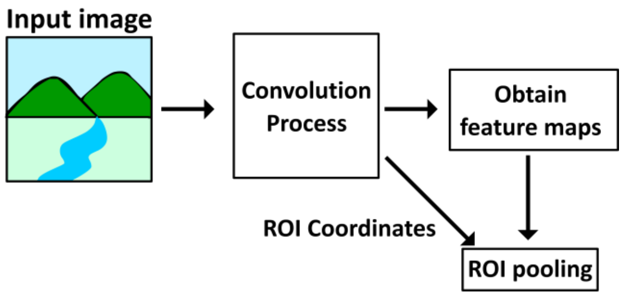

Figure 4. An object detection process with region of interest (ROI) pooling

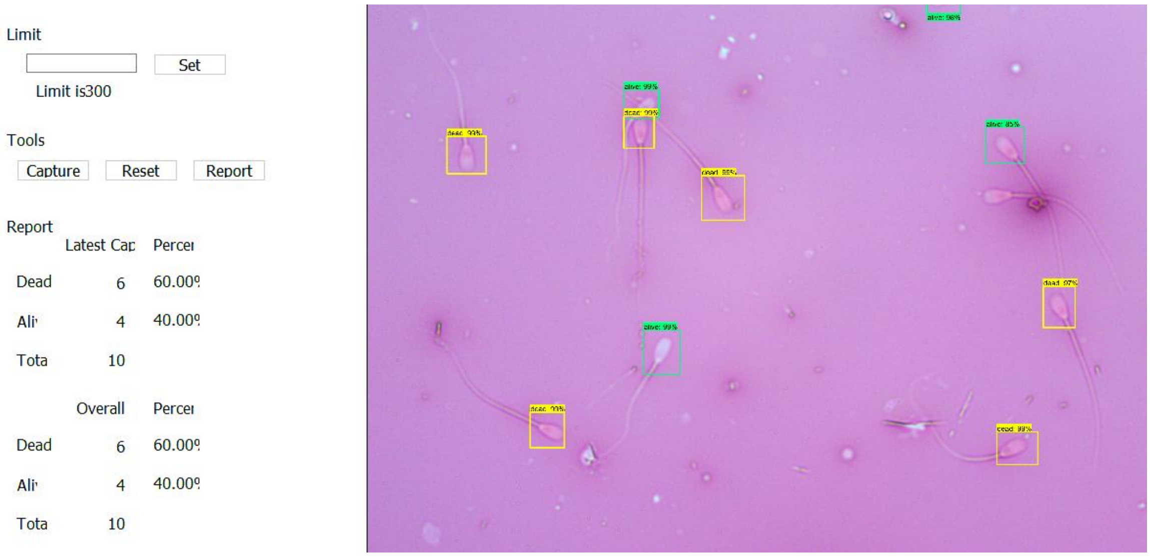

Figure 5. Illustration of the system detected the viability of the bull sperms in the input data, including a statistical data report

III. Experiments and Results

In this research, we developed sperm detection and the viability classification models. We contained the sperms into the glass slide and captured the images of the sperms by the glass slide. We collected 800 images as a training set and 200 images as a test set. In addition, experts checked the actual number of the sperms in this dataset and recorded a summary of statistical data as shown in Table I. Furthermore, we developed a model based on Faster RCNN. We showed an example of the result on the model in Fig. 6.

Here, we separated the experiments into two sets: Set 1 and Set 2. Set 1 represented the experiment of sperm detection and the viability classification models without the preprocessing process. Set 2 represented the experiment of sperm detection and the viability classification models included the preprocessing process. The results of detection and classification for both experiments showed on Table II and Table III.

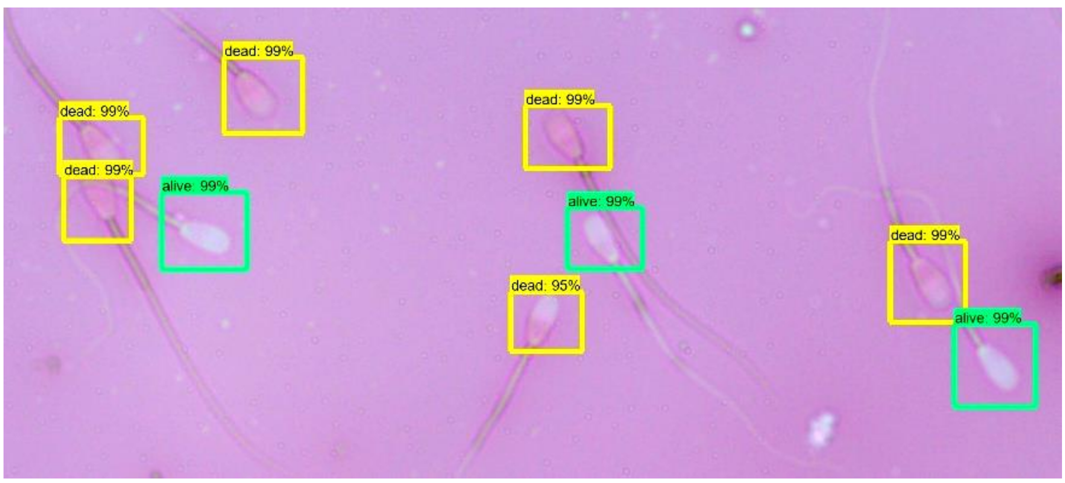

Figure 6. Example of results from the developed model

TABLE I. AN ACTUAL NUMBER OF SPERMS FROM IMAGES PRESENTING IN THE TRAINING SET AND THE TEST SET

	Alive	Dead	Total
Training set	2,566	3,975	6,541
Test set	750	1,006	1,756
Total	3,316	4,981	8,297

TABLE II. A NUMBER OF SPERMS IN THE TEST SET ON SET 1 USED IN THE SPERM DETECTION MODEL

	Amount	Percentage
The actual number of sperms	1,756	-
Accuracy of sperm detection	1,593	90.72%
Accuracy of sperm classification	1,346	84.49%
	Overall performance	76.65%

In the Set 1, we evaluated the performance of the model in term of the sperm detection and the viability classification data excluded the preprocessing step in the test set (Table II) and the confusion matrix (Table IV). The result showed that sperm detection model detect the amount of sperm is 1,593 of 1,756 in the test set (90.72%). After detecting sperm, the result showed the accuracy of the viability classification model is 1,346 of 1,593 (84.49%). Finally, the result showed the accuracy of the overall models is 1,346 of 1,756 in the test set (76.65%).

TABLE III. A NUMBER OF SPERMS IN THE TEST SET ON SET 2 USED IN THE SPERM DETECTION MODEL

	Amount	Percent
The actual number of sperms	1,756	-
Accuracy of sperm detection	1,557	88.67%
Accuracy of sperm classification	1,064	68.34%
	Overall performance	60.59%

TABLE IV. A CONFUSION MATRIX OF SPERMS CLASSIFICATION (SET 1)

		Actual Data	
		Positive (Alive)	**Negative (Dead)**
Predicted Data	**Positive (Alive)**	709	193
	Negative (Dead)	54	637

TABLE V. A CONFUSION MATRIX OF SPERMS CLASSIFICATION (SET 2)

		Actual Data	
		Positive (Alive)	**Negative (Dead)**
Predicted Data	**Positive (Alive)**	571	296
	Negative (Dead)	197	493

In Set 2, the experiment for the system included the preprocessing step had been validated by measuring the number of correct detection and classification (Table III) and a confusion matrix (Table V) as same as Set 1. We found that the correctness of sperm detection had reduced to 88.67%, and the classification accuracy was only 68.34%. Then, the accuracy of the overall system was 76.65%.

IV. DISCUSSION

In this study, we proposed a detection and classification systems for assessing the viability of the bull sperms using the technique in deep learning, called Faster RCNN. The 1,000 images of sperms were the input data of the system captured using a compound microscope at 40X. The system processed the sperm classification automatically based on various colors on the head of the sperms.

We conducted two sets of the experiments as called Set 1 and Set 2. The experimental results of the detection showed that the performance of Set 1 outperformed to Set 2. The accuracy of the detection on Set 1 was up to 90.72%; whereas Set 2 was 88.67%. Moreover, the accuracy of the classification on Set 1 was 84.49%; whereas Set 2 was only 68.34%. Fig. 7 illustrates a comparison the performance between the Set 1 and the Set 2. Set 1 provided overall performance better than Set 2. That means the preprocessing step may be not necessary for the system. These findings surprised us because, based on the fact, the performance of the detection and classification models is dependent on the quality of the input data. The preprocessing step should help to refine the input data. We used the edge sharpens and color and brightness contrast sketching to emphasize the appearance of the objects existing in the image that included junks and uninterested objects. Therefore, this is possible that the system may misclassify the object because some features of the objects and junks have been similar. Furthermore, the preprocessing step using image processing techniques may decrease image quality that also lessens important image information. Since it is necessary to find a suitable preprocessing method for the data.

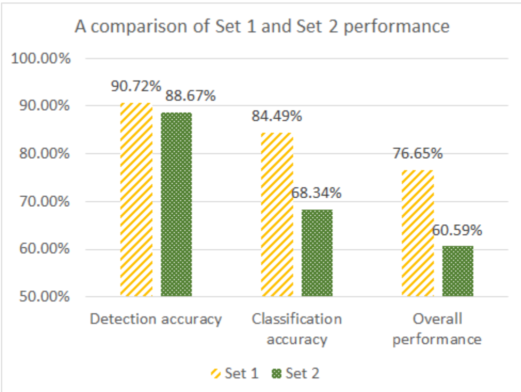

Figure 7. A comparison of the detection and classification performance on the Set 1 and Set 2

On the Set 1, as observed the result of the sperm viability classification, the correctness was up to 84.49%. With this accuracy, it was obvious that the system was capable to use in the real-world scenarios. However, an error of the classification was explicit. We observed that the error occurred due to a misunderstanding of the system and data inconsistency. For example, the image is captured from the glass slide and strained by the viability that causes the head of the dead sperms colored. Unfortunately, the color at the head of the sperm was

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sometimes not obvious. This problem can be minimized if we increased the size of the trained data or training epochs.

This study has an impact on the research on a bioinformatics area because the system is applicable to the real-world data. Moreover, based on the detection result, the system can distinguish between junks and the object effectively. However, there is a limitation. The input image should be clear and focused. This means that the interest object should be dominant and others should be blurred. Unfortunately, a quality of the input image is mostly depended on the performance of the compound microscope.

V. Conclusion

In this study, we utilized the Faster RCNN to detect the bull sperms on the glass slide and classify the viability of the sperms as dead or alive automatically. The data used to train the model was collected by capturing 1,000 images on the 40X of the compound microscope. For the evaluation, we split the data into the train (800 instances) and the test (200 instances) datasets. We conducted the experiments to validate sperm detection and the viability classification. Based on the experimental results in Set 1, we obtained the high accuracy for sperm detection, 90.72%. Moreover, the accuracy of the viability classification was 84.49%. This clarified that the system was applicable to apply to the real-world dataset with a dominant performance.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Pumrapee Poomka and Kittipat Sriwong implemented the method and conducted the experiments; Prakaidoy Ditsayabut and Chokchai Wanapu are experts who advised and commented on this successive study; Satidchoke Phosaard advised about the research project; Sarunya Kanjanawattana and Watthana Pongsena proposed the method, designed the solution to solve any problems during the study as well as wrote the manuscript including approved the final version of the manuscript.

Acknowledgment

We would like to show our gratitude to Mr. Satidchoke Phosaard for assisting and sharing wisdom with us during the research.

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