Automatic Healthy Sperm Head Detection using Deep Learning

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***Abstract*—Infertility is one of the diseases in which researchers are interested. Infertility disease is a global health concern, and andrologists are constantly looking for more advanced solutions for this disease. The intracytoplasmic sperm injection (ICSI) process is considered as one of the most common procedures for achieving fertilization. Sperm selection is performed using visual assessment which is dependent upon the skills of the laboratory technicians and as such prone to human errors. Therefore, an automatic detection system is needed for quick and more accurate results. This study utilizes a deep learning technique for the classification of heads of human sperms which indicate the healthy human sperms. The Convolutional Neural Network (CNN) model of visual Geometry Group of 16 layers (VGG16) was used for classification, and it is one of the best architectures used for image classification. The dataset consists of 1200 images of human sperm heads divided into healthy and unhealthy. Here, the VGG16 model is fine-tuned and achieved an accuracy of 97.92% and a sensitivity of 98.82%. Moreover, it achieved an F1 score of 98.53%. The model is an effective and real-time system for detecting healthy sperms that can be injected into eggs for achieving successful fertilization. This model quickly recognizes healthy sperms and makes the sperm selection process more accurate and easier for the andrologists.**

Keywords*—Infertility; sperm morphology; deep learning; human sperm head; healthy sperms

I. Introduction

The inability of couples to achieve pregnancy after 1 year of regular coition is known as infertility [1]. Infertility is the problem of most couples around the world, about 30-40% of them related with male factor abnormalities [2]. The most important role in the intracytoplasmic sperm injection method is the selection of the best sperms that can be injected into the oocytes. Embryologists select the best sperm depending on the morphology of sperms by visual assessment. This process is time-consuming and so tiring compared to machine learning approaches [3]. Machine learning depends on manual extraction of features such as head area, length, and width of sperms [4]–[6]. The human sperms are composed of head, midpiece and tail. The head of human sperm contains the deoxyribonucleic acid which carries the genetic instructions needed for reproduction. The midpiece part has the mitochondria to supply the tail with energy required for movement. The tail part provides the sperm with motility required for its movement to oocytes for fertilization [34]. The tip of head contains acrosome which secretes enzymes that are useful for penetration and make the penetration process easier for human sperms.

Intracytoplasmic sperm injection (ICSI) process is considered as an optimum choice with male infertility diseases. ICSI process is done when the sperm count is low, and it is also preferable when the sperms have low motility according to the semen analysis. In Vitro Fertilization (IVF) process is different from ICSI since the fertilization is performed by the sperms themselves in the test tube without injection with any needles after keeping the human sperms with oocytes inside one tube [35]. Intrauterine Insemination (IUI) process is less costly in which the semen is injected directly into the uterine cavity and this method increases the success rate of pregnancy with some cases [34].

The rest sections of this paper is organized as follows: Section 2 discusses the literature review. Section 3 describes the methodology, dataset, and explanation of preprocessing stages in detail. Section 4 explains the proposed model for healthy sperm detection. Section 5 shows and discuss the results of this proposed model. Section 6 concludes the paper and mentions the scope of future work.

II. Literature Review

There are several researches about automatic detection of the best sperms used for the intracytoplasmic sperm injection process using machine learning and deep learning. In one of these studies, J Riordon et al. improved a model for classification of sperms using VGG16 using versatile dataset with accuracy reached 94.1% [9]. Javadi et al. proposed a method for sperm evaluation with 3 labels which are acrosome, head and vacuole [10]. Mirroshandel et al. improved automatic detection algorithm for human sperm images with accuracy reached 93.2% with tail and neck [11]. Revollo, Natalia V., et al. improved an automatic system for human sperm head detection using machine learning techniques in which the sperms were labeled manually achieving an accuracy of 92% [36]. Bijar et al. proposed a model for segmentation of different parts of sperms with high accuracy [12]. Erfan Miahi et al. developed a neural architecture search based on genetic algorithm for detection of different parts of human sperm with an accuracy of 91.66% and 77.33% in the vacuole and head abnormality detection, respectively [37]. Prabaharan, L., and A. Raghunathan. proposed a convolutional neural network for abnormal sperm detection based on morphology achieving an accuracy of 98.99% [38].

There are some researchers who used K-nearest neighbor and principal component for sperm analysis [7]. Several researches have proven the relationship between ICSI success

and the morphology of the sperm head [8]. In some studies, stained sperms were used, and they are not useful for the intracytoplasmic sperm injection **(**ICSI) process, but this method has the advantage of detecting healthy sperms easily and it is more suitable for low quality and noisy images [14].

There are also many researchers used versatile types of deep learning architectures; liu et al. used AlexNet architecture for classification of human sperms [13]. McCallum et al. improved a VGG16 model for detecting the best sperms of highest integrity of DNA [14]. Ghasemian et al. proposed a model for recognition of sperm abnormality with low computation time [15]. Some studies used segmentation procedures, shaker et al. proposed a method for detection and segmentation of human sperms achieving accuracy of 92% for sperm head segmentation [16]. Urbano et al. presented a model for tracking of human sperms [17]. Mirsky et al. developed a system for healthy and unhealthy sperm detection based on morphology using machine learning with precision of 90% [18]. Thirumalaraju et al. presented a deep learning model with accuracy of 89% in recognition of good sperms [19]. These algorithms could automate the process of sperm recognition with its types [14]. For computer vision tasks, there are many algorithms for transfer learning performed by researchers to find out the best processes for the image classifiers [22], [23]. The design of the neural network affects the accuracy of the classification, depending also on the type of dataset. Baker et al. used reinforcement learning in designing neural network architectures [24], zoph et al. also updated a neural network architecture using reinforcement learning [25]. Zoph et al. used versatile methods for producing the best architectures for classification of images and proposed learning architectures for image recognition [21].

Mathematical morphology is so important for sperm recognition and detection of healthy and unhealthy sperms. Rodríguez et al. used Lambertian model and sperm cell segmentation based on mathematical morphology [28]. There are several research studies that are interested in counting the sperms using versatile methods. One of these works is the method of Susrama, I. G., K. E. Purnama, and M. H. Purnomo, which proposed a model for human sperm concentration and number using Otsu's threshold obtaining an accuracy of 91% [29]. There are some models for processing microscopic videos for detecting the motility of sperms [30]. It is helpful for tracking of the spermatozoa through the videos and this analysis is needed for motility assessment. Boumaza et al. improved an automatic system for concentration assessment based on decision trees machine learning [31]. Ilhan et al. presented an approach for analyzing spermiogram tests with high correlation with visual assessment results and proposed an algorithm for motile sperm detection [32]. Lv, Qixian, et al. proposed an algorithm for automatic segmentation of sperm head based on the U-Net network [39]. Chandra, Satish, et al. utilized different deep learning models, and both ResNet50 and VGG19 models achieved an accuracy of 71%, 87.33%, 73% for acrosome, vacuole and head label, respectively [40].

The intracytoplasmic morphologically selected sperm injection (IMSI) usually is done using magnification of 10,000 and it has the property of motile spermatozoa selection properly [26]. Several researches demonstrated the effectiveness of IMSI over ICSI process due to the power of magnification of IMSI process and many factors that differ from patient to another. So, IMSI process in some cases showed clinically significant difference [26]. There are many factors that influence the success of intracytoplasmic sperm injection process, the World Health Organization (WHO) defined the criteria of reference values for the characteristics of semen. The reference volume of semen is 1.5 mL, reference sperm count is 15 million per mL and minimum total motility of 40% [27], [34]. The abnormalities of sperm heads can cause failure of fertilization, and then failure of ICSI process [8].

III. Material and Methods

A. Sperm Head Dataset

The Dataset used is freely available for public, collected from Hannam Fertility Centre in Canada and utilized by McCallum et al [14]. Some processing work was done on dataset before using, and then the dataset has been classified into healthy and unhealthy human sperm heads with the help of andrologists as shown some of dataset in Fig. 2. Google Colab in python is mainly used for implementing this paper with the aid of MATLAB program. Dataset is partitioned into training set, test set and validation set. The dataset consists of 1200 images of size 150x150 pixels and partitioned as 720 images for training, 240 images for test purpose and 240 images for validation purpose, as represented in Fig. 1, and Table I.

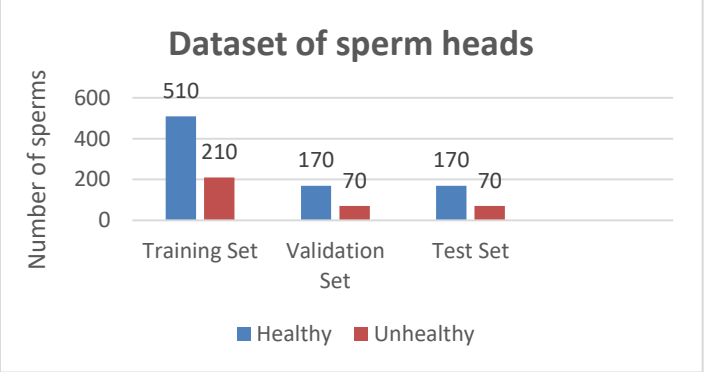

Fig. 1. Overview of Sperm Head Dataset with Healthy and Unhealthy Classes.

TABLE I. Partitioning of Dataset

Dataset Partitions	Number of Images	Percentage
Training Dataset	720	60%
Validation Dataset	240	20%
Test Dataset	240	20%
Total Dataset	1200	100%

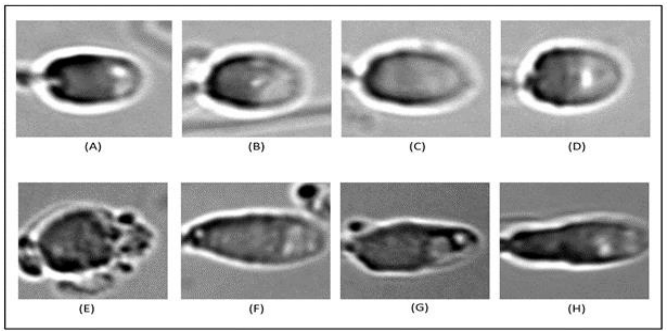

Fig. 2. A Selection of Sperm Head Dataset. (A), (B), (C), (D) Healthy Sperm Head Images. (E), (F), (G), (H) Unhealthy Sperm Head Images.

B. Image Preprocessing

Preprocessing of images is an important step for image enhancement (e.g., noise removal), the median filter is used for this purpose [33] as represented in Fig. 3. Image resizing also is necessary in the preprocessing steps. Dataset images were scaled up to 224x224 pixels according to VGG16 requirements. Image resizing has an important role in image processing technique to enlarge or reduce the dataset. Image interpolation can be divided into two different ways, both image down sampling and image up sampling are necessary when resizing the dataset for matching the requirements of the deep learning model and differ according to each model and the field of study.

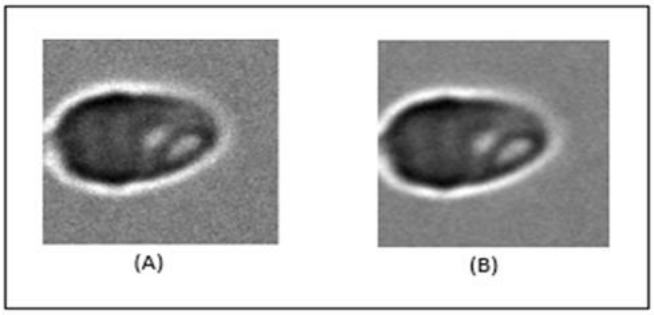

Fig. 3. Preprocessing of Input Images. (A) Noisy Image before Preprocessing. (B) Image after Applying Median Filter for Noise Removal.

The main preprocessing methods used after denoising process are explained as the following.

1) Otsu's thresholding process: In this technique, the thresholding on grayscale image is processed. Otsu's method is used to perform automatic image thresholding by obtaining the image histogram and computing the threshold value (t) then the image pixels is replaced into white or black depending on the value of the threshold (t) [29]. The image pixels whose saturation is greater the threshold is replaced into white and image pixels whose saturation is lower than the threshold is replaced into black color. It searches for the threshold that reduces the intra-class variance as shown.

$$\sigma_\omega^2(t) = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t) \quad (1)$$

where σ_ω^2 is the intra-class variance, ω_0 and ω_1 are the probabilities of the two classes separated by a threshold (t) and σ_0^2 and σ_1^2 are the variances of these two classes.

This method is considered as one of segmentation techniques in image processing and this algorithm can be described as the following.

Otsu's thresholding algorithm:

a) Given grayscale image.

b) Calculate the histogram of this image.

c) Computing the probabilities of each intensity level

d) Set up initial ω_i and μ_i at t = 0

e) Calculate ω_i and μ_i at all possible thresholds. (t = 1, t = 2, … till the maximum intensity)

f) Calculate $\sigma_b^2(t)$ as the following equation:

$$\sigma_b^2(t) = \sigma^2 - \sigma_\omega^2(t) = \omega_0(t)\omega_1(t)[\mu_0(t) - \mu_1(t)]^2 \quad (2)$$

where σ_b^2 is the inter-class variance, ω is the class probabilities and μ is the class means.

g) Choose the best threshold value for optimum results corresponding to the maximum $\sigma_b^2(t)$ and apply this threshold to image [29].

2) Area opening method: Area opening technique is used for removal of objects with area smaller than a specified parameter from the foreground of binary images [33]. Mathematically, opening a set A by a structuring element B can be given by the following equation.

$$A \circ B = (A \ominus B) \oplus B \quad (3)$$

where the symbol $\ominus$ denotes to erosion and $\oplus$ denotes to dilation.

Area opening technique is utilized for removing vacuoles that may appear in the head of sperms in order not to affect the accuracy of the classifier of the proposed model as shown in Fig. 4, and this method contributes to get high accuracy.

3) Image complement process: The complement of a black and white image is converting the zeros to ones and ones to zeros [33]. Image complement is performed for getting white sperm head and black background as shown in Fig. 5. The image complement is used as a final step before training in which data augmentation is done through.

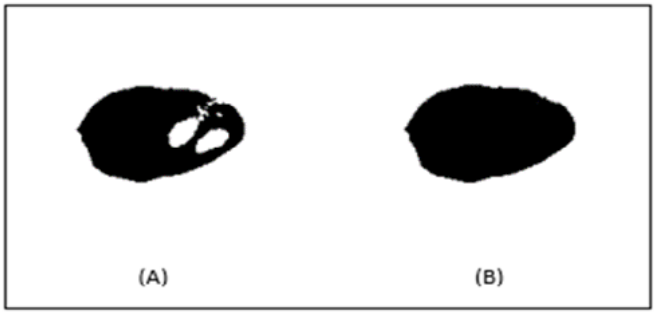

Fig. 4. Area Opening of Input Images. (A) Image after Applying Otsu's Thresholding Segmentation Method and before Applying Area Opening. (B) Image after Applying Area Opening for Removing Vacuoles in Sperm Head.

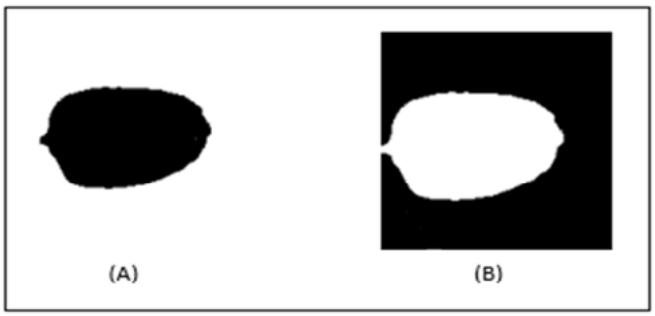

Fig. 5. Image Complement of Input Images. (A) Image after Applying Area Opening Process. (B) Image after the Complement Process.

4) Data augmentation: Image data augmentation is a technique used to increase the dataset by modifying images. Image data augmentation is performed only on training dataset. This is done by using ImageDataGenerator that is provided by Keras deep learning library. ImageDataGenerator class is used for augmentation of images with some parameters of image augmentation (e.g., shift, zoom and rotation) as represented in Table II. Some of these modifications for each parameter and its effect on the original images are shown in Fig. 6.

TABLE II. PARAMETERS OF DATA AUGMENTATION

Parameters	Values
Rescale	1./255
Width shift range	0.2
Height shift range	0.2
Horizontal flip	True
Zoom	0.25
Rotation	-30°
Image fill	"Nearest"

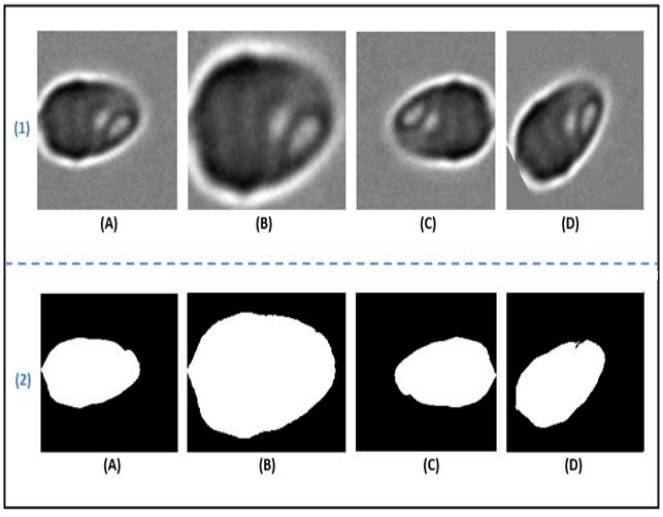

Fig. 6. Some Types of Image Augmentation Applied to Dataset. The First Row in Group (1) Including the Raw Dataset before Segmentation and the Second Row in Group (2) Including the Images after Segmentation (A) Original Image without Augmentation. (B) Image with Zoom Augmentation. (C) Image with Horizontal Flip. (D) Image with -30° Rotation.

IV. PROPOSED HEALTHY SPERM HEAD DETECTION MODEL

The deep learning architecture VGG16 is a convolutional neural network model proposed by Simonyan et al. [20] and pre-trained on ImageNet. The size of the input image of this architecture is fixed 224x224x3 then the image is passed through a stack of convolutional layers and the filter used of size 3x3 [9]. At first it has two convolution layers with pooling layer then another two convolution layers with pooling followed by three convolution layers with pooling repeated three times and finally three layers of fully connected (FC) attached with the output layer (e.g., sigmoid function) as shown in Fig. 7. In this proposed model, new layers are considered. Flatten layer, dense, dropout, dense and dropout layer are added respectively, and then dense layer with sigmoid activation function is used as represented in Fig. 8.

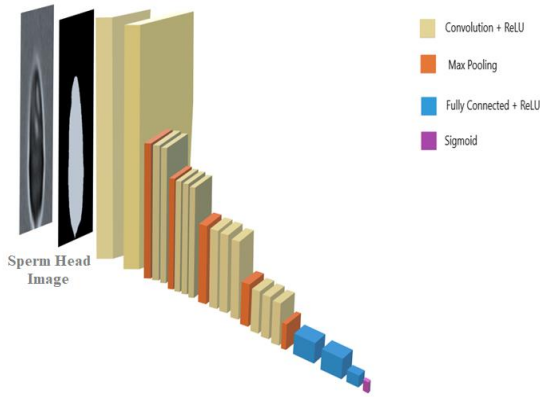

Fig. 7. General Representation of VGG16 Architecture.

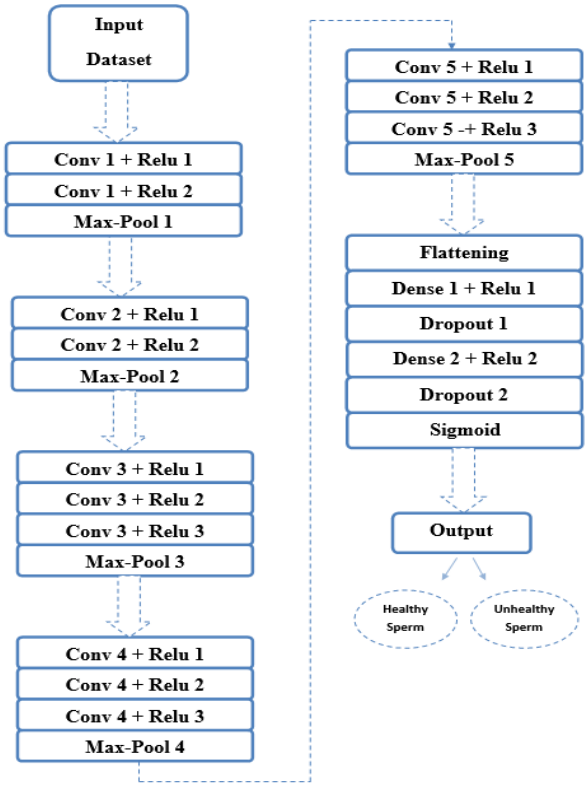

Fig. 8. Fine-Tuned Proposed Model for Healthy Sperm Head Detection.

The features of sperm head were extracted by convolutional layers, each convolutional layer has the same size of kernels [10]. Given an image H of size (u, v), the convolution can be estimated as follows,

$$G(u,v) = (H * Q)(u,v) = \sum_x \sum_z M(u - X, v - Z)Q(x,z) \quad (4)$$

where Q is the convolution kernel of size x, G is the feature map of the output, H is the feature map of the input and (u, v) is the size of image.

In this proposed model, binary cross entropy loss function is performed since we have only 2 output categories, binary cross entropy loss function is used during adjusting the weights of the model, and then the loss can be minimized [10], this function is effective for optimizing the model and it is represented as the following formula.

$$E = -\frac{1}{n} \sum_{i=1}^{n} [\, y_i \cdot log(\hat{y}_i) + (1 - y_i) \cdot log(1 - \hat{y}_i) \,] \quad (5)$$

where n is the number of scalar values in the model output, y_i is the true label, $\hat{y}_i$ is the predicted label.

The proposed algorithm demonstrated its effectiveness in classification of healthy and unhealthy sperm head then detecting the best healthy sperm head which indicates the best healthy sperm that can be used for successful fertilization as proved in andrology [34]. The main steps of the convolution and the VGG16 algorithm can be summarized as the following.

	1) **Steps of Convolution algorithm are:**
a)	The first step is to multiply the filter with the region of the input image of the same size using the convolution formula.
b)	Each element is multiplied with an element in the corresponding location then the results will be summed and give one output value.
c)	Repeating these steps by sliding the filter across the image until getting the final output.

	2) **Main steps of VGG16 algorithm are:**
a)	2D Convolution as previously described.
b)	Max Pooling. This operation is used for down sampling feature maps by calculating the maximum value in each patch of a feature map.
c)	Flattening, converting pooled feature map to a one-dimensional array (vector).
d)	Dense layer. It's a layer that consists of neurons that detect input from neurons that's in the previous layers.
e)	Dropout Layer. Used to prevent a model from overfitting.
f)	Activation function that finally used for defining the output [10]. In the last layer, the sigmoid function is used for the classification of sperms healthy or unhealthy. The sigmoid function is expressed as the following, $S(x) = \frac{1}{1+e^{-x}}$ (6) where $S(x)$ is the sigmoid function of a variable x

In this paper, the best sperms could be recognized using this proposed model. At the first, the dataset was uploaded. The preprocessing steps were done to be handled by VGG16 and they were effective in this process. The noises in the image were removed using median filter, the sperm heads were segmented using Otsu's thresholding process, area opening was implemented for removing objects in the heads, the images were complemented, and then the model training and evaluation were done. Consequently, any image can be inserted after preprocessing for detection as shown in the proposed model flowchart in Fig. 9. There are also preprocessing steps should be done to the input images.

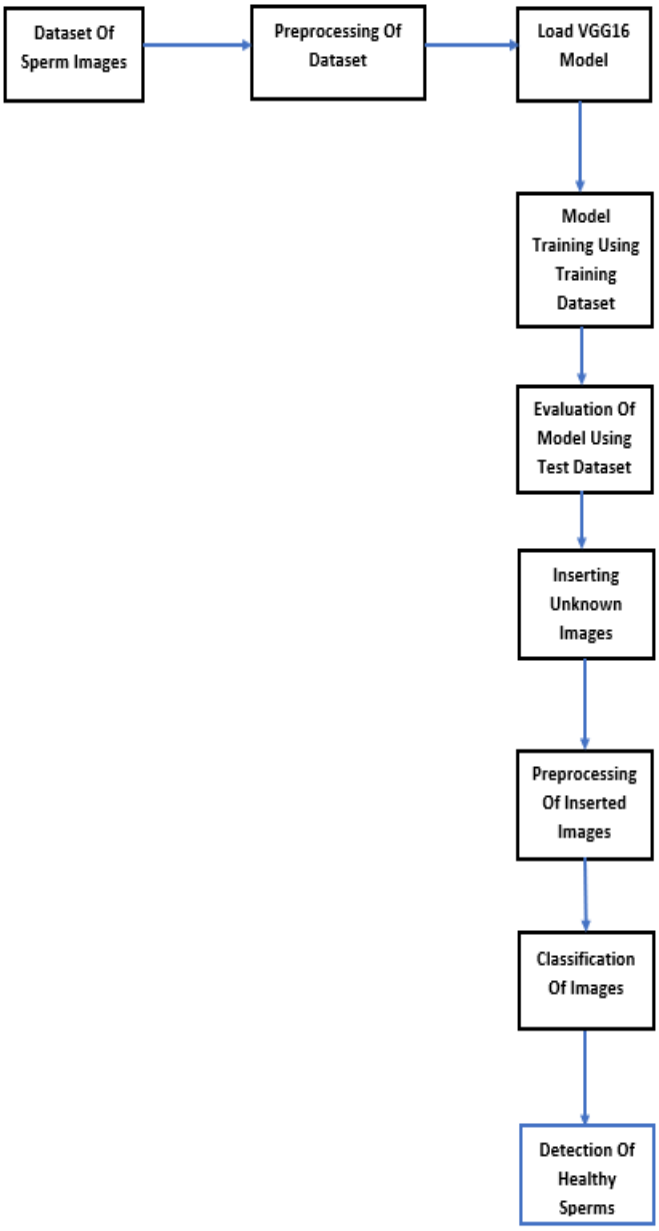

Fig. 9. Flowchart of the Proposed Model for Healthy Sperm Detection.

V. Results and Discussion

The proposed model for classification of sperm heads is effective after using 1200 images of healthy and unhealthy sperm heads resulting in high accuracy. This proposed model is trained on a large dataset, and it is a real time system for andrologists for classification of healthy and unhealthy sperms. In Fig. 10, the results of the proposed model are shown for 4 unknown images of healthy and unhealthy sperm heads which are detected accurately. In this study, the median filter demonstrated the effectiveness of image denoising. Otsu's thresholding process is done for segmentation then area opening technique is done and both have proved their success with the dataset. The accuracy of model reaches 97.92%, sensitivity equals 98.82%, precision equals 98.25%, specificity equals 95.71% and F1 Score equals 98.53% as shown in Table IV. The following formulas [7]–[11] respectively represents Accuracy, Sensitivity, Precision, Specificity and F1 Score. The following confusion matrix shows the values of True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) [11]. The confusion matrix of our study is shown in Table III with 168 true positive and 67 true negative. The performance of our model is shown in Fig. 11 with high training and validation accuracy after training with 200 epochs respectively reached 99.51% and 98.48%. The training and validation loss respectively reached 0.9817 and 1.4251.

TABLE III. The Confusion Matrix on the Test Set

		Predicted	
		Healthy	***Unhealthy***
Actual	***Healthy***	TP = 168	FN = 2
	Unhealthy	FP = 3	TN = 67

$$Accuracy = \frac{TN+TP}{TN+TP+FP+FN} \quad (7)$$

$$Sensitivity = \frac{TP}{TP+FN} \quad (8)$$

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

$$Specificity = \frac{TN}{TN+FP} \quad (10)$$

$$F1\ Score = \frac{2*Precision*Sensitivity}{(Precision+Sensitivity)} \quad (11)$$

TABLE IV. Evaluation Parameters for the Proposed Model

Classifier	**Accuracy**	**Sensitivity**	**Precision**	**Specificity**	**F1 Score**
Proposed Method	97.92%	98.82%	98.25%	95.71%	98.53%

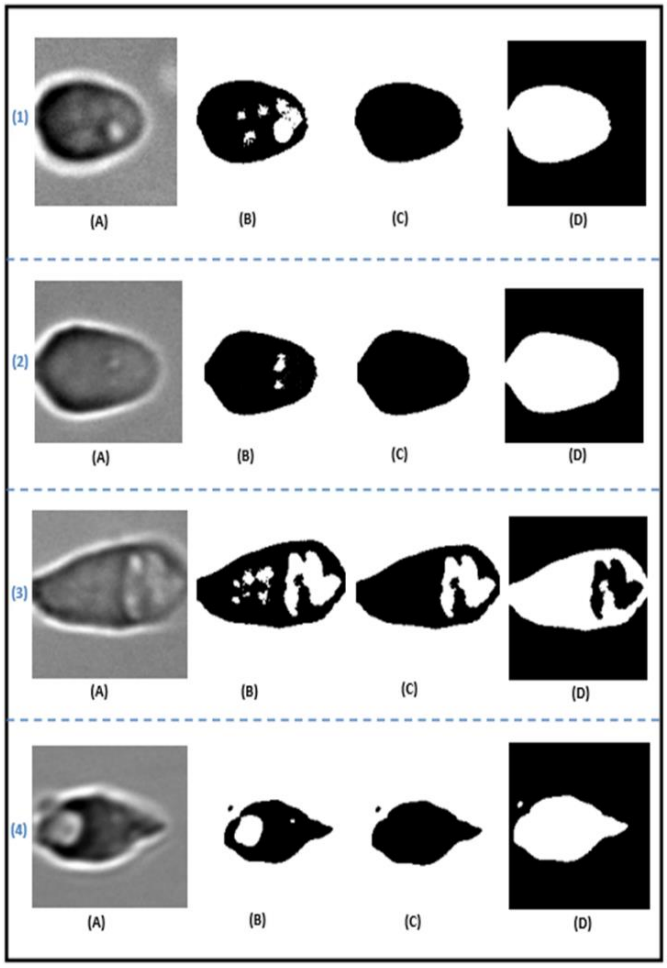

Fig. 10. Results of the Proposed Model with Preprocessing Steps of Four Images in which the Images in Groups (1) and (2) are Healthy Sperm Heads and the Images in Groups (3) and (4) are Unhealthy Sperm Heads. (A) Original Images before Segmentation. (B) Images after Applying Otsu's Thresholding Segmentation. (C) Images after Applying Area Opening. (D) Images after the Complement Method.

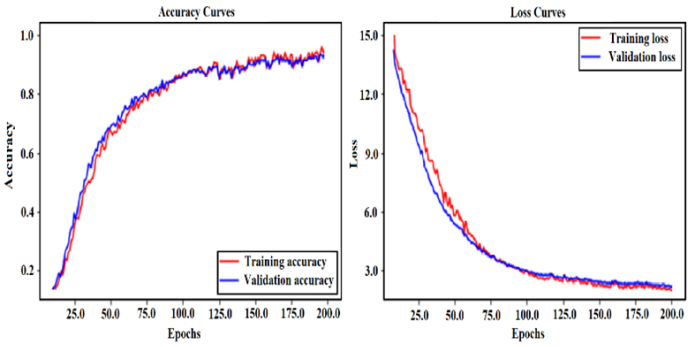

Fig. 11. Performance of the Proposed Model.

VI. Conclusion and Future Work

In conclusion, the best sperms required for the ICSI process can be selected using the proposed deep learning model. Laboratory specialists always look for simple and precise methods for healthy sperm recognition for injection into oocytes process. This paper proposed a deep learning method based on VGG16 and its results have been approved by the andrologists. In this article, deep learning approach demonstrated the effectiveness of healthy sperm detection rather than machine learning. The fine-tuned VGG16 model resulting in high accuracy of 97.92% and this is one of the main advantages of this proposed model compared to the results of other models in literature review section. The VGG16 transfer learning model has proven its computationally efficiency for sperm head recognition. Assisted reproductive technology (ART) is necessary for finding more tools for the detection of the best sperms for increasing fertilization, pregnancy, and live birth rates. This proposed approach demonstrated its advantages of getting rapid results with high accuracy for detecting the healthy sperm heads which indicate to the healthy sperms that can be used in the intracytoplasmic sperm injection process.

For future work, different deep learning architectures can be used with a comparative study among them with using versatile dataset for better and more accurate evaluation. Taking another part of sperm into consideration with different preprocessing methods can be useful.

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