Cattle Sperm Classification Using Transfer Learning Models

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***Abstract*— This paper focused on classifying sperm and white blood cells (WBC) through image processing by utilizing different architectures of Transfer Learning Model (TLM). The researchers used microscopic images of sperm for image classification. There are 602 total image datasets used for training and testing of different convolutional network models in deep learning. These models are: InceptionResNetV2, Xception, DenseNet121, DenseNet169, MobileNetV1, InceptionV3, and DenseNet201. The classification of sperm and WBC is successfully implemented. In the evaluation of these models, the following is observed: confusion matrix, loading time, weight size, and accuracy. Through these evaluations: the highest model to recall for true positive is InceptionResnetV2. The accuracy of 98.3% is obtained by this model. However, the DenseNet121 has also comparable results with 95% accuracy considering its weight size of 93.49 MB compared to InceptionResnetV2 of 641.93 MB.**

***Keywords*— Convolutional Neural Network; Deep Learning; Transfer Learning; Cattle Sperm Classification; Morphology; White Blood Cells**

I. Introduction

The cattle industry is one of the world's most vital agricultural enterprises. It includes the production of cattle for several purposes, including beef, hides, dairy, and other products. According to a Cornell University professor, William Lesser, cattle had been trained for a thousand years and it had allocated the early community with four essential purposes. These are supply of high-grade protein, the means to stock foodstuffs indirectly expendable by humans, skins for clothing and shoes and motive (traction) power [1].

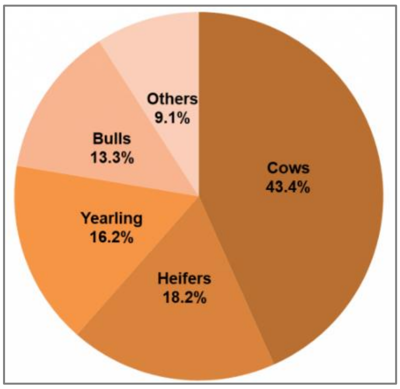


Fig. 1 Distribution of Cattle Inventory as of January 2019
(Source: psa.gov.ph)

As stated in the cattle situation report of Philippine Statistics Authority as of January 01, 2019, the inventory of cows was estimated at 1.10 million heads. In Fig. 1, 43.4 percent was total cattle stocks, as the remaining 56.6 percent were impacted by heifer, yearling, bulls, and others (castrated and ready to breed bulls) [2].

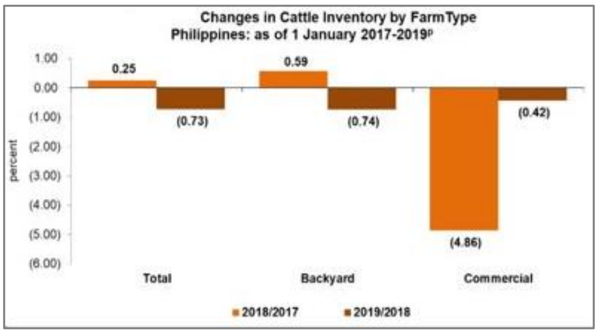


Fig. 2 Changes in Cattle Inventory by Farm Type
(Source: psa.gov.ph)

Fig. 2 shows the changes in cattle inventory from 2017-2019. The overall cattle stock was 2.54 million heads compared to the earlier year's statistics of 2.55 million heads, there was a 0.73 percent decrease [2]. Hence, infertility of a cattle really is one of the major hindrances in livestock production for it directly affects dairy farm profitability and the improvement of national economy, as well as the lifestyle in the rural and urban communities.

Infertility in cattle is defined as the reduced or absent ability to produce viable offspring. Infections that reduce ovulation rates, fertilization rates, embryonic survival rates, fetal survival rates or perinatal survival rates result in observed infertility in cattle [3].

The procedure for herd infertility examination consists evaluation of breeding history, feeding and management practices, and examination of health records, herd, and laboratory results to make an objective diagnosis [4]. In addition, low fertility is generally accepted because of cryopreservation [5]. The reduction develops from both a lower viability post-thaw and sublethal dysfunction in a proportion of the surviving subpopulation. The causes for the loss of fertility are different.

Computer-assisted semen analysis produce values for sperm parameters more rapidly and accurately than those acquired with traditional semen analyses methods. Computer and video technologies have advanced rapidly in modern years; hence, the capability and accuracy of the latest versions of

CASA systems are significantly better, and they give more information about the different motion characteristics of spermatozoa. Because of the vital role of sperm motility in the reproductive process, such systems will enable us to move into a new era of diagnostic andrology and predict the fertilizing capability of semen [6].

There are several literatures relating to feature extraction used in sperm classification using the artificial neural network. An evaluation of fertility data where the penetrak and zona-free hamster egg penetration assay were used [7]. A seminal quality prediction where they utilized a genetic algorithm to optimize the structure of artificial neural network to classify the semen samples [8]. Fertility quality prediction based on Sperm Whale Optimization Algorithm (SWA) [9]. A novel deep learning algorithm for malformation detection of sperm morphology using human sperm cell images [10].

Cattle semen analysis is performed as part of breeding. The proponents, together with the help of San Juan, Batangas Municipal Agricultural Office Farmer's Information and Technology Services (FITS) Center in data gathering, will perform deep learning using transfer learning models to visually infer whether it is normal, abnormal or WBC by getting images obtained manually from the microscope and classify each image to its right category.

II. Literature Review

A. Deep Learning

Deep Learning is a recognized machine learning tool and was mostly used in several applications for solving different complex problems that require high accuracy and sensitivity, particularly in the medical field that paid a lot of researchers' attention in the past few years. In the paper where brain tumor was classified through deep learning, Convolutional Neural Network (CNN) is one of the widely used deep learning architectures for classifying a dataset of 3064 T1 weighted contrast-enhanced brain MR images for grading (classifying) the brain tumors into three classes (Glioma, Meningioma, and Pituitary Tumor) [11].

In the paper "Study of Detection of Various types of Cancers by using Deep Learning: A Survey", the proponents concluded that the only way to reduce the death ratio of cancer, is by early detection of it. Deep learning methods were used by the author of 22 papers which helps to detect the cancer early [12].

B. Transfer Learning

Transfer Learning is a common method in deep learning given the immense resources required to train deep learning models. It is the development of learning in a new task over the transfer of information from a related task that has already been learned [7].

C. Keras Platform

In the study "Fully convolutional networks for segmenting images from an embedded camera" [13], Python, Keras, and Theano was used in implementing and prototyping Fully Convolutional Networks. This paper explains an FCN to part images from a compact stereo imaging sensor attached to a robot to provide low-level computer vision functions.

The Keras Library was used to pattern the network's architecture, speeding up the process of finding a network with good accuracy and low consumption of computational resources. They used the transfer learning technology to retrain the flower category datasets, which can greatly improve the accuracy of flower classification.

D. Xception

Xception is an Inception-inspired deep convolutional neural network. It somewhat surpasses InceptionV3 on the ImageNet dataset and on a larger image classification dataset including 350 million images and 17,000 classes [14].

E. DenseNet121

In the research "Classification of TrashNet Dataset Based on Deep Learning Models" [15], deep learning models were used to classify recyclable garbage and the best results were found in the DenseNet121 using fine-tuning with a test accuracy rate of 95%.

F. InceptionResNetV2

This is the ensemble of three residual and one InceptionV4.It is developed by Christian Azegedy, Sergey Ioffe, Vincent Vanhoucke and Alex Alemi [16]. In the study "PolyNet: A Pursuit of Structural Diversity in Very Deep Networks" [17], the researchers presented a new family of modules, namely the PolyInception.

G. DenseNet169

The DenseNet169 architecture was proposed by Huang et al. [18]. In the study "Pneumonia Detection Using CNN based Feature Extraction" [19], The DenseNet169 model has capability of accessing feature maps from all of its preceding layers, hence, it produces best results.

H. MobileNetV1

MobileNetV1 has depthwise convolution applies a single filter to each input channel. It also has a standard convolution which both filters and inputs combines into a new set of outputs in one step. [20]

In the study "Driver distraction detection using single convolutional neural network" [21], the researchers used CNN model like MobileNet to detect driver distraction. Though the system results varied greatly on how fast CPU/GPU processing time is, the results for MobileNet accuracy rather than InceptionResNet is observed to be higher.

I. InceptionV3

In the research "Inception-v3 for flower classification" [22], the proponents used Inception-v3 model of TensorFlow platform to classify flowers. The classification accuracy of the model is 95% on Oxford-I7 flower dataset and 94% on Oxford102 flower dataset, which is higher than other method.

J. DenseNet201

In the study "Comparison of two different deep learning architectures on breast cancer" [23], two different deep learning methods are assessed on the breast cancer dataset. There are 20748 images for training and 5913 images for testing and based on the results acquired, DenseNet-201 architecture has an accuracy of 92.24%.

III. METHODOLOGY

A. Microscopic Analysis

Microscopic analysis is performed since it is very important in semen analysis. It measures the quality and quantity of the moving cells called sperm. Therefore, the clinical condition determines the extent of analysis for accurate results.

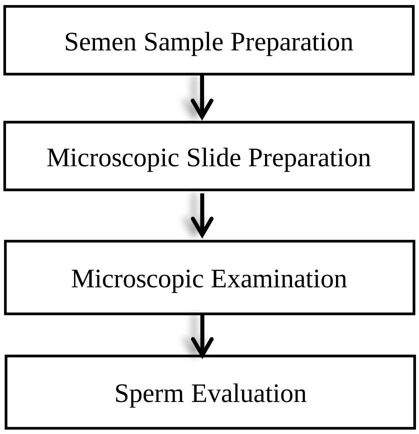


Fig. 3 Steps in preparation for semen analysis

Fig. 3 shows the preparation of semen analysis. The semen sample which is the main input of the system will be placed in a slide. The semen to be used should be as fresh as possible to avoid the disintegration of semen constituents. Consistency on the volume of sediment that is placed on the slide must be properly observed. The recommended volume for the conventional glass-slide method is 6 µL (0.006 mL) covered by an 18 × 18 mm glass cover slip (if a 22 x 22 coverslip is used, the volume of the semen on the microscope slide should be 10 µL [24]. The semen undergoes microscopic analysis for the sperm concentration, morphology, and motility.

B. Microscopic Images

The images used in this study are images collected from the microscope. Fig. 4 shows a sample of images of sperm classified as normal and abnormal, and the WBC.

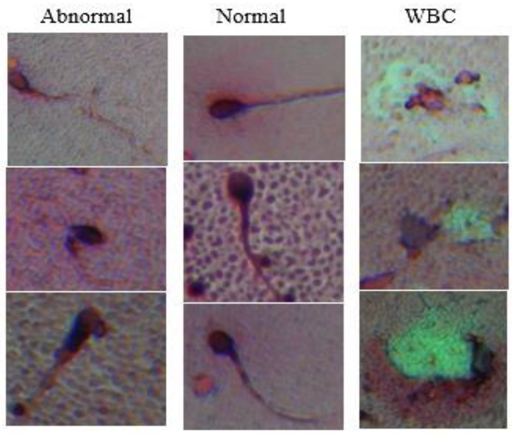


Fig. 4 Sample images of dataset: Abnormal, Normal, and WBC

C. System Model

The system model of the study starts at loading the datasets to the base model. The models used in the study are: Xception, DenseNet121, InceptionResNetV2, DenseNet169, MobileNetV1, InceptionV3, and DenseNet201. The datasets have three categories: normal sperm, abnormal sperm, and WBC. The network is now trained and tested to classify the datasets according to its category. After the testing, the classifier is now loaded to the system and is used to classify per category. Each category is evaluated per convolutional model.

D. Data Collection

The microscopic images of the semen samples are collected using the microscope with 4x and 10x magnifier. There is a total of 602 images and the breakdown is shown in Table I.

TABLE I. DATASET

Semen Sample	Number of Images	Train Data	Test Data	Validation Data
Normal Sperm	234	187	47	46
Abnormal Sperm	214	171	43	45
White Blood Cells	154	123	31	31
Total	**602**	**481**	**121**	**120**

The dataset is divided to 80% for training and 20% for testing. The validation data is collected from either the training data or testing data also.

E. Experiment: Feature Extraction, Training and Testing

Keras platform will be used with Tensorflow backend in coding system. The proponents limit the epoch of 80.

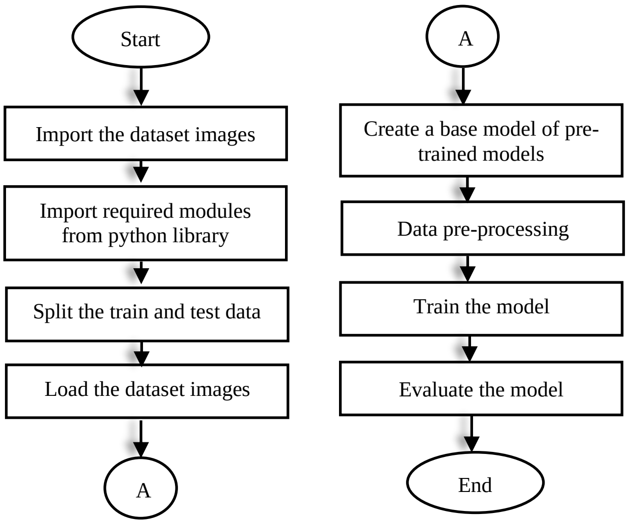


Fig. 5 Program flowchart of the python code

As shown in Fig. 5, the program starts at organizing imports such as numpy, keras, sklearn, and matplotlib. Then, Split the training and testing data by configuring the dataset into specific directories. Third, is to load sperm images from subfolders of category. Next, create a base model of different pre-trained CNN. Then, acquire the features by pre-processing the data. Next, is to configure the training and testing of the model. Lastly, after training, different architectures will be evaluated and compared based on model accuracy, comparison of losses, confusion matrix, loading time, and weight size to verify what is the best model for the sperm morphology and WBC classification.

The input images differ for each model. The usual shape of a convolutional model is a rectangular prism. This is equal to the product of width, height, and depth. The input image differs for each model. The input image is equal to the product of the size of the image and the number of channels. The number of channel is 3 for colored images and 1 for black and white images. Table II shows the size of input images for each model.

TABLE II. INPUT FOR EACH MODEL

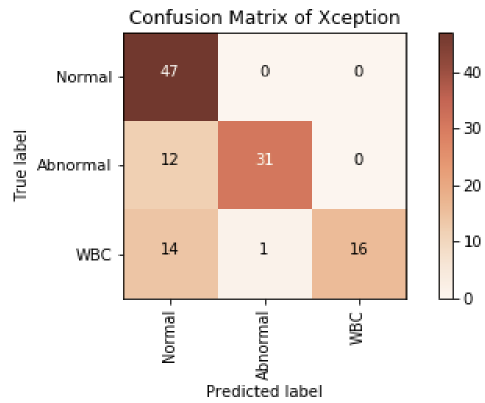
Model	Input Image
Xception	224x224x3
DenseNet121	224x224x3
InceptionResNetV2	224x224x3
DenseNet169	224x224x3
MobileNetV1	224x224x3
InceptionV3	299x299x3
DenseNet201	224x224x3

IV. RESULTS

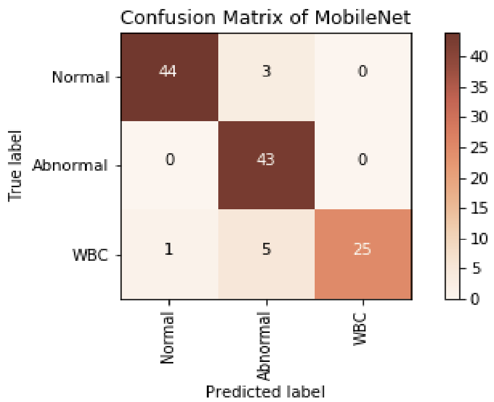
To compare and verify the effectives of each pre-trained convolutional neural networks, following criteria was observed: Confusion matrix, loading time, accuracy, and weight size.

A. Confusion Matrices

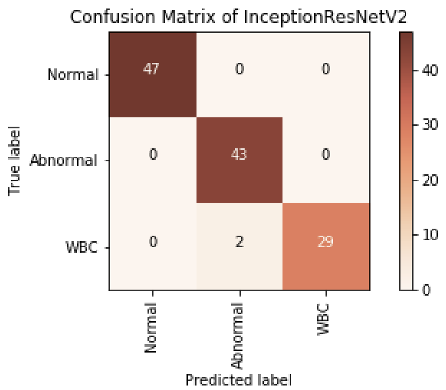
The confusion matrix is named also as matching matrix, where a row signifies a predicted class and the column signifies the actual class [25]. This demonstrates the misclassification similarity between the different convolutional neural networks. The Fig. 6 shows the confusion matrices of different models over the 3 classes for sperm morphology and WBC.



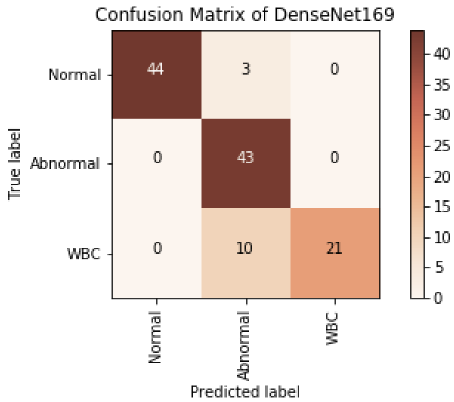
(a) Xception



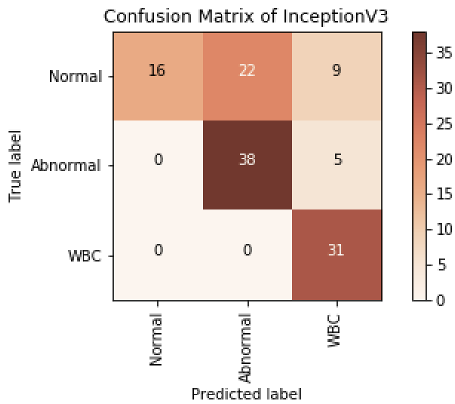
(b) MobileNet



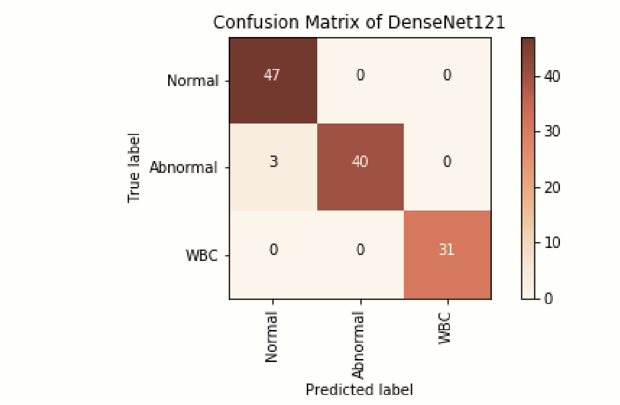
(c) InceptionResNetV2



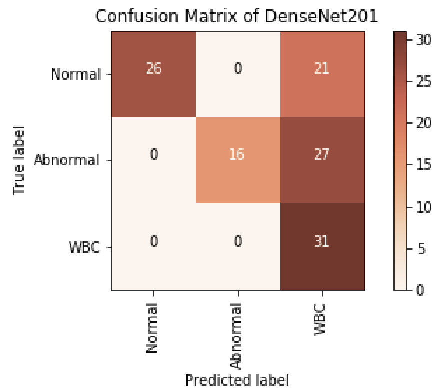
(d) DenseNet169



(e) InceptionV3



(f) DenseNet121



(g) DenseNet201

Fig. 6 Confusion Matrix of the Sperm and WBC Classification of Different Convolutional Network Models: (a) InceptionResNetV2, (b) DenseNet121, (c) MobileNetV1, (d) DenseNet169, (e) Xception, (f) InceptiontV3 and (g) DenseNet201

B. Weight Size, Loading Time and Accuracy

In the table shown below, the highest performing model is the InceptionResNetV2 with an accuracy of 98.3%.

TABLE III. EVALUATION OF MODELS

Model	Weight Size (MB)	Loading time (seconds)	Accuracy (percent)
InceptionResNetV2	641.94	10.961	98.3
DenseNet121	93.49	7.372	95.0
MobileNet	26.79	1.389	92.6
DenseNet169	165.16	10.753	89.3
Xception	262.96	2.513	77.7
InceptionV3	274.36	4.748	70.2
DenseNet201	233	12.876	60.3

While DenseNet121 and MobileNet have an accuracy of 95% and 92.6% respectively, it is still analogous with the execution of InceptionResNetV2. It is also considered that these models have the least size in terms of weights compared to all models.

V. Conclusion

This study used transfer learning in sperm morphology and WBC classification. Pre-trained models were used such as Xception, DenseNet121, InceptionResNetV2, DenseNet169, MobileNetV1, InceptionV3, and DenseNet201. The sperm images used were taken manually which include: Normal, Abnormal and WBC. The result shows that InceptionResNetV2 has the highest accuracy of 98.3%; however, the very lightweight models are DenseNet121 and MobileNet have an analogous accuracy of 95% and 92.6% with a very fast loading time of 7.372 and 1.389 seconds, respectively.

Acknowledgment

The authors would like to thank the Technological University of the Philippines-Manila, specifically the Electronics Engineering Department for their support to students. And most of all, the Almighty God for giving them strength, enthusiasm, and wisdom to complete this study.

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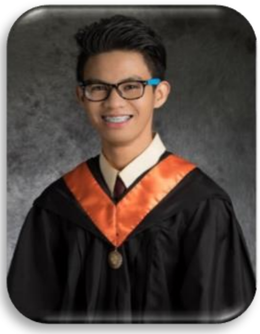

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