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SPERM ABNORMALITY CLASSIFICATION USING MULTI-PURPOSE IMAGE EMBEDDING AND CLASSICAL MACHINE LEARNING

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Abstract (10pt)

Since sperm cells have big impact for the human welfare in terms of reproduction, there are many studies have been done. In this case, we are attracted to enrich the method in determining the morphological properties of them using machine learning. Most study about it is done using 2-steps action that are feature extraction which is continued by classification. In our work, we aimed to lower the complexity by using image embedding as a general-purpose feature extractor that requires no training. For feature extraction using image, it is found that RGB has better performance compared to grayscale if we want to use Support Vector Machine (SVM). Meanwhile, when a comparation is done between SVM, random forest, Multi Layer Perceptron (MLP), Naïve Bayes, and k-Nearest Neighbour (kNN) for classification process, MLP shows the best performance among them which is around 85%. Moreover, our proposed method has low complexity in such a way that it requires low training time.

Keywords: *sperm cells morphology, machine learning, feature extraction, classification, support vector machine, multi layer perceptron.*

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1 INTRODUCTION

The shape of sperm cells has an impact to the fertility of human. Several studies have been conducted to observe the phenomenon. It is found that sperm defects were more commonly found in infertile men [1]. Similar study also suggested that sperm from fertile men contained more normal sperm (sperm without any defect) compared to those of infertile men [2]. Therefore, morphology property of sperm plays important role in estimating the success of assisted reproduction [3], [4]. Similarly, in vivo conditions, higher pregnancy rate is expected when the sperm had good morphology. In addition, good morphology also correlated with shorter time to pregnancy in a natural condition [5].

According to World Health Organization (WHO) standard [6], sperm morphology is assessed by human in a laboratory using a light microscope with magnification of x1000. The technician needs to assess at least 200 spermatozoa and classifies them according to their shape. However, human-based estimation poses a risk of inconsistency. A study conducted in Australia revealed a variability in morphology estimation between laboratories [7]. A similar pattern was also found in Italy [8], Belgium [9], and Spain [10].

The reproducibility limitation of manual sperm assessment leads to the development of an automated one, commonly referred as Computer Aided Semen Analysis (CASA). In general, a CASA system consists of three components: a camera, microscope, and image processing system [11]. Currently, CASA systems have been deployed in many labs around the world. The benefits of CASA systems are reduced subjectivity and human error [12], the ability to process more sample, reducing analysis time, and increasing productivity [13].

Several methods have been developed to estimate morphology properties of sperm cells. Yüzkat et al. [14] aggregated the result of six Convolutional Neural Network (CNN) models using two fusion technics. A similar ensembled approach was also conducted by combining four CNNs (VGG16, VGG19, ResNet34, and DenseNet-161) with a meta classifier [15]. Yang et al. [16] implemented BlendMask framework for extracting individual cell, then used SegNet to segment a cell into head, midpiece, and principal piece comments. A classification was then performed by EfficientNet based on the sperm components. Similarly, U-Net was adopted to segment a spermatozoa into head neck, and tail [17]. However, no classification was performed to estimate the morphology. A VGG-like network was proposed to perform morphology classification [18], [19].

Most methods for morphology determination involved deep neural networks (DNN), especially CNNs to perform the task due to their effectiveness to extract features from images. The training procedure was completed either from scratch or using transfer learning. The former uses specific sperm-related dataset to train a randomly initiated network [14], [17] while the latter takes benefit of pre-trained network using generic dataset such as ImageNet and retrained using subject-specific dataset [15], [19].

Although CNN have good performance in general use case, including in sperm image classification, it requires a lot of time for training due its massive number of parameters to be trained. An experiment mentioned that retraining process in a transfer learning approach took around 30 minutes and 2 hours per fold for dataset consisting of 216 and 1132 images, respectively [19]. In general, a more complicated architecture such as ensembled models demands more training time.

In practice, it is not always necessary to train a CNN on a specific set of images that are very similar to the test set. It is sufficient to train on large data set with wide variation to achieve comparable performance [20]. This concept leads to the development of image embedding that uses pretrained CNN on large dataset such as ImageNet as feature extractor [21]. It works by trimming the final classifier network of a CNN so that it produces a fixed length of vector that acts as a feature for further processing. The use of image embedding and various machine learning algorithms has been studied and work well in several areas, such as image clustering [22], medical image classification [23], and remote sensing image classification [24].

This study aims to identify morphology type of a sperm cell using image embedding as a feature extractor to reduce training time. We compare various machine learning algorithms for classification to identify the performance of each algorithm for this specific case. Last, we also compare the performance of our approach with similar methods.

2 RESEARCH METHOD

2.1 Overview of the methods

Our proposed method consisted of two main parts: the feature extractor and classifier. The feature extractor part received RGB image and emits feature vector at a certain length. The other part, classifier mapped the feature vector into one of categories that defines the condition of a sperm cell: abnormal, normal, and non-sperm. The feature extractor was implemented using image embedding, while the classifier made use of classic machine learning algorithms for faster training time.

2.2 Image Embedding

Image embedding attempts to transform pixel representation of an image into a feature vector. Ideally, the vector captures the visual characteristics and semantics of the image. The basic mechanism to build image embedding involves deep learning technique, such as CNNs [25].

In a general scenario, image embedding model was built by training a CNN model in classification tasks. Any CNN model can be used as feature extractor in image embedding, such as VGG, ResNet, Inception, and SqueezeNet. After training is completed, the output layer is truncated and activations from preceding layers are extracted, normalized, and concatenated to form a feature vector. The resulting vector is immune to image transformation, brightness variation, and noise [26]. Therefore, it is an ideal input for various machine learning method.

SqueezeNet [27] is a CNN model that aims to provide high accuracy with minimal parameters. It applies a fire module consisting of 1x1 and 3x3 convolution filters to reduce the number of parameters. The architecture comprises of a convolutional layer followed by 8 fire module and a final convolutional layer. By doing so, it can achieve comparable performance to the AlexNet with 50x fewer parameters. Table 1 compares the performance and parameters of several CNN models [28]. It is evident that SqueezeNet has much fewer parameters than other competitors with comparable performance. Therefore, it is an excellent option for building an image embedding.

Table 1. Comparison Of Parameters and Performance Of Several CNN Architectures

Model	Number of Parameters	Top-5 Accuracy on ImageNet
VGG 16	138M	89.8%
VGG 19	143M	89.8%
ResNet 18	11.7M	89.45%
ResNet 34	21.8M	91.4%
Inception V3	23.8M	93.9%
SqueezeNet	3.2M	88.20%

2.3 Classification Algorithms

In machine learning, classification aims to assign a category to a data point in mutually exhaustive and mutually exclusive manner. Several algorithms are suitable for classifying feature vectors from image embedding into one available class in sperm defects categories.

a. Support Vector Machine (SVM)

SVM tries to build hyperplane that maximally separates datapoint according to their class labels, thus it is usually referred as maximum margin classifier [29]. In binary classification, given training pairs $\{x_i, y_i\}_{i=1}^n$, where $x_i \in \mathbb{R}^N$ and $y_i \in \{-1,1\}$, SVM solves the Formula 1

$$min\left\{\frac{1}{2}\|w\|^2 + C\sum_i^n \xi i\right\} \quad (1)$$

SVM uses kernel trick to transform the data from their original space into higher dimensional one. Occasionally, the data is not linearly separable. Therefore, mapping to higher dimensional space may find linearly separable hyperplane. Several popular kernels are: linear, polynomial, sigmoid, gaussian radial basis function, and randomized blocks analysis of variance [30].

Original SVM is only able to perform binary classification with only two classes. Extension to the classic algorithm was made by introducing strategies such as one-against-all, one-against-one, and multiclassification objective functions.

b. Random Forest

Random forest classifier is a collection of decision tree classifier that perform majority vote for the output for each individual tree. Each tree is populated from data randomly selected from training data using bagging technique. The feature is also carafully selected using technique such as Infromation Gain Ratio criterion or Gini Index [31].

The random forest tree is grown by first selecting a sample from the training data. Then, a decision tree is built from the sample data by repeatedly selecting a number of features from the sample, selecting the best split, and split the node into two branches. These steps are repeated until an interation threshold is reached [32].

c. Naïve Bayes

Naive Bayes classifier uses the basic principle of Bayes theorem [33]. For a datapoint x, the probability of the data is assigned class k (C_k) is expressed as:

$$p(C_k|x) = \frac{p(C_k)p(x|C_k)}{p(x)} \quad (2)$$

In case of continuous data, the likelihood is assumed to have normal distribution. Thus, the likelihood is calculated using Formula 3

$$p(x|C_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} e^{-\frac{(v-\mu_k)^2}{2\sigma_k^2}}. \quad (3)$$

The class of a datapoint is determined by the maximum posterior, as in Formula 4.

$$\hat{y} = \underset{k\in\{1,\ldots,K\}}{\operatorname{argmax}}\, p(C_k)\prod_{i=1}^n p(x_i|C_k) \quad (4)$$

d. K-Nearest Neighbor (kNN)

Unlike other classifiers, kNN does not build a model during its proces because it does not actually have training process. kNN works under assumption that the class of a datapoint is similar to that of data around it, using a concept called neighborhood [34]. The neighborhood concept is based on distance measure. The distance of two datapoints x and y can be calculated using several distance measures, such as Euclidean, Manhattan, and Chebyshev, as stated in Formula 5-7.

$$d(x,y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2} \quad (5)$$

$$d(x,y) = \sum_{i=1}^n |x_i - y_i| \quad (6)$$

$$d(x,y) = \max_i(|x_i - y_i|) \quad (7)$$

kNN determines a category of a test data discovering k nearest neighbor after calculating the distance of the test data to each data in the training data. The class is determined by the majority class of the k nearest neighbors.

e. Multi Layer Perceptron (MLP)

MLP is a type of neural network consisting of three or more layers. They are one input layer responsible for handling the input data, one or more hidden layer, and an output layer that perform calculation and non-linearization. The non-linear computation is created by an activation function [35]. An illustration of an MLP with one input layer for 4 features, one hidden layer with 2 neurons, and one output layer with 3 output neurons is available in Figure 1.

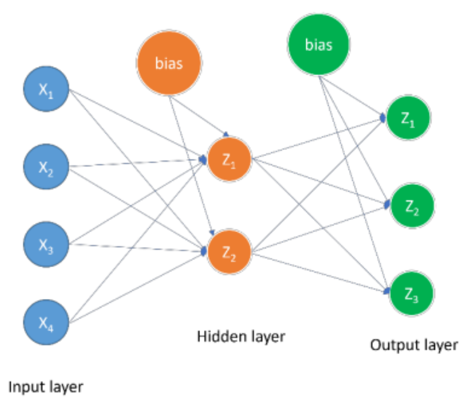


Figure 1. Illustration of an MLP network

2.4 K-Fold Cross Validation

After training a model, it is important to measure the generalization of the model, i.e. how it performs in unseen test data. Cross-validation is a well-known method to assess the performance of the model. In this scenario, the overall dataset is split into two portions, one of them is used for training while the rest is for testing [36].

K-fold cross validation divides the dataset into *k* equal partitions. One portion is allocated for testing while the others are for training. This process is repeated *k* times and the performance of each iteration is averaged.

2.5 Evaluation Metrics

Several measures exist to judge how well a classifier works. Most common measures are precision, recall, and F1 score. They are calculated by comparing the output of the classifier to the actual class. The comparison can be summarized in a matrix called confusion matrix, as illustrated in Figure 2.

	Actual Positive	**Actual Negative**
Predicted Positive	True Positive (TP)	False Positive (FP)
Predicted Negative	False Negative (FN)	True Negative (TN)

Figure 2. Illustration of Confusion Matrix

Based on a confusion matrix, precision is defined as ratio of predicted positive data that are acutally positive while recall means ratio of positive data that are correctly predicted as positive. Last, F1 score is the weighted mean of precision and recall. Precision, recall, accuracy, and F1 score are expressed in Formula 8-11 [37].

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

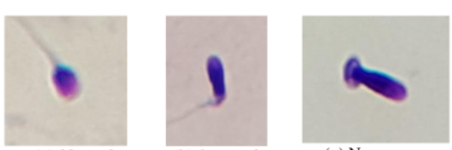
$$Recall = \frac{TP}{TP+FN} \tag{9}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{10}$$

$$F1 = \frac{2.Precision.Recall}{Precision+Recall} \tag{11}$$

2.6 Dataset

This research employs Sperm Morphology Image Data Set (SMIDS) [38] containing 3000 images of single sperm cells with their associated morphology type. There are three categories, normal sperm, abnormal sperm, and non-sperm. Sample of the dataset for each category is depicted in Figure 3. The distribution of the image in each class considered balance, as explained in Table 2.



(a) Normal (b)abnormal (c) Non-sperm

Figure 3. Sample image for each category

Table 2. Data distribution per class.

Class	Number of data
Normal	1021
Abnormal	1005
Non-sperm	974

2.7 Experiment Setting

The proposed method is implemented using Orange [39] datamining toolbox version 3.37.0. For extracting features from image, image embedding based on SqueezeNet is used. The network was trained using ImageNet dataset. In order to have fair evaluation, the training and testing scheme is set to 10-fold cross validation. Hyperparameters for each machine learning model are available in Table 3 - Table 6.

Table 3. Hyperparameters for SVM.

Hyperparameter	Value
Cost	1.00
Epsilon	0.1
Kernel	RBF
Iteration limit	100

Table 4. Hyperparameters for Random Forest.

Hyperparameter	Value
Number of trees	100
Min subset split	5

Table 5. Hyperparameters for MLP.

Hyperparameter	Value
Neurons in hidden layer	128
Activation	ReLu
Solver	Adam
Max iteration	200

Table 6. Hyperparameters for kNN.

Hyperparameter	Value
Number of neighbors	5
Metric	Euclidean
Weight	Uniform

3 RESULTS AND DISCUSSION

3.1 Image Color Type

The first experiment was conducted to see if the number of color channel affects the performance of the classification algorithm. To do so, we train SVM classifier on RGB and grayscale images and evaluate the result using 10-fold cross validation.

Table 7 displays performance comparison of SVM train on RGB and grayscale images. For all evaluation metrics, it is shown that the use of RGB images improve the performance of SVM classifiers. However, the gain is not significant, just by a mere of 3.91%. It may be caused by the fact that the type of defects in sperm cell can be sufficiently observed by grayscale images. If an implementation needs higher performance, using RGB images is recommended. But, if speed is the priority, grayscale images are better option.

Table 7. Classification performance on RGB dan grayscale image

Metric	Grayscale	RGB
Precision	0.749	0.773
Recall	0.741	0.771
Accuracy	0.741	0.771
F1	0.742	0.771

3.2 Comparison Between Classification Algorithms

Second experiment was carried out to identify the best for classifying defects in sperm cell images. Five classic machine learning algorithms: SVM, random forest, MLP, naive bayes, and kNN were trained and evaluated using 10-fold cross validationon RGB images. Each algorithm were trained and evaluated using the same split to maintain consistency.

Table 8 compares the performance of each algorithm in classifying the sperm data. MLP achieved the best performance indicated by the highest F1 score. Only MLP and random forest were able to obtain more than 80% of F1 score. MLP is suitable for this purpose because it is able to represent non-linear function and estimate any function given a hidden layer with sufficient nodes. In addition, the dataset contains 3000 images with 1000 features that are sufficient to avoid overfitting and underfitting. Also, the architecture is simple, to avoid the effect of vanishing gradient.

Table 8. Performance comparison on several classifiers

Algorithm	Precision	Recall	Accuracy	F1
SVM	0.773	0.771	0.771	0.771
Random Forest	0.821	0.814	0.814	0.816
MLP	**0.854**	**0.854**	**0.854**	**0.854**
Naïve Bayes	0.760	0.755	0.755	0.757
kNN	0.802	0.788	0.788	0.790

Table 9 shows the classification performance for each class in the dataset using MLP. From the F1 score, the classifier worked best in recognizing non-sperm cells. Visually, the shape on non-sperm cells is easy to differentiate from sperm cells. Therefore, the classifiers can spot the different easily. On other hands, the difference of normal and abnormal is less obvious. In several cases, the difference comes in the absence or shape of some part of sperm cells. In the end, it becomes more difficult to recognize by a classifier.

Table 9. Classification performance on each class

Class	Precision	Recall	F1
Normal	0.831	0.856	0.843
Abnormal	0.814	0.811	0.813
Non-sperm	0.921	0.895	0.908

3.3 Comparison with other methods

We also compared the result of our proposed method with those of similar approach on the same dataset. Two previous works from Ilhan et al. [40] and Yüzkat et al. [14] were taken as comparison. Ilhan et al. used SURF and MSER feature descriptors and SVM as classifiers, while Yüzkat et al. developed ensembled model from 6 CNN models.

Table 10 shows comparison of the performance of the proposed methods with similar ones. Our approach yield comparable result witht those of Ilhan et al. However, we use general purpose feature extractor rather than handcrafted feature that may not generalize well. Conversely, the proposed method from Yüzkat et al. produced noticeable improvements. However, the method involved a combination of 6 CNN model that are expensive to train. Among all models, the simplest one was trained for 11 hours with some of them had training time of twice of the time. In comparison, the combination of feature extraction and a classification algorithm in our proposed method took no more than 5 minutes to complete.

Table 10. Performance comparison with other methods

Method	Accuracy (%)
Ilhan et al. (SURF)	85.1
Ilhan et al. (MSER)	85.7
Yüzkat et al. (No augmentation)	66.45
Yüzkat et al. (8x augmentation)	90.2
Proposed	85.4

4 CONCLUSION

In this study we proposed a simple yet effective way to recognize sperm morphology from sperm cells images. Our proposed method resulted in a balance of performance and simplicity. We achieve the accuracy of 85.4% with low training time. This finding is applicable for sperm morphology identification with sensitive time constraints and limited hardware since it does not require GPU and the inference computation is simple.

Further research should be directed to identify important features generated by image embedding since it contains 1000 variables. It is also useful to add explainability aspect to the proposed method since its implementation in medical field usually demands reasoning for the classification.

5 REFERENCE

[1] J. Auger, P. Jouannet, and F. Eustache, "Another look at human sperm morphology," *Hum. Reprod.*, vol. 31, no. 1, pp. 10–23, Jan. 2016, doi: 10.1093/humrep/dev251.

[2] R. Menkveld, C. A. Holleboom, and J. P. Rhemrev, "Measurement and significance of sperm morphology," *Asian J. Androl.*, vol. 13, no. 1, pp. 59–68, Jan. 2011, doi: 10.1038/aja.2010.67.

[3] T. Kruger and K. Coetzee, "The role of sperm morphology in assisted reproduction," *Hum. Reprod. Update*, vol. 5, no. 2, pp. 172–178, Mar. 1999, doi: 10.1093/humupd/5.2.172.
[4] G. Cito *et al*., "Sperm morphology: What implications on the assisted reproductive outcomes?," *Andrology*, vol. 8, no. 6, pp. 1867–1874, Nov. 2020, doi: 10.1111/andr.12883.
[5] S. Oehninger and T. F. Kruger, "Sperm morphology and its disorders in the context of infertility," *FS Rev*., vol. 2, no. 1, pp. 75–92, Jan. 2021, doi: 10.1016/j.xfnr.2020.09.002.
[6] World Health Organization, *WHO laboratory manual for the examination and processing of human semen*. Geneva: World Health Organization, 2021.
[7] P. Matson, M. Kitson, and E. Zuvela, "Human sperm morphology assessment since 2010: experience of an Australian external quality assurance programme," *Reprod. Biomed. Online*, vol. 44, no. 2, pp. 340–348, Feb. 2022, doi: 10.1016/j.rbmo.2021.11.005.
[8] E. Filimberti *et al*., "High variability in results of semen analysis in andrology laboratories in Tuscany (Italy): the experience of an external quality control (EQC) programme," *Andrology*, vol. 1, no. 3, pp. 401–407, 2013, doi: 10.1111/j.2047-2927.2012.00042.x.
[9] U. Punjabi, C. Wyns, A. Mahmoud, K. Vernelen, B. China, and G. Verheyen, "Fifteen years of Belgian experience with external quality assessment of semen analysis," *Andrology*, vol. 4, no. 6, pp. 1084–1093, 2016, doi: 10.1111/andr.12230.
[10] C. Álvarez *et al*., "External quality control program for semen analysis: Spanish experience," *J. Assist. Reprod. Genet*., vol. 22, no. 11, pp. 379–387, Dec. 2005, doi: 10.1007/s10815-005-7461-2.
[11] R. Finelli, K. Leisegang, S. Tumallapalli, R. Henkel, and A. Agarwal, "The validity and reliability of computer-aided semen analyzers in performing semen analysis: a systematic review," *Transl. Androl. Urol*., vol. 10, no. 7, Art. no. 7, Jul. 2021, doi: 10.21037/tau-21-276.
[12] R. P. Amann and D. F. Katz, "Andrology Lab Corner: Reflections on CASA After 25 Years," *J. Androl*., vol. 25, no. 3, pp. 317–325, 2004, doi: 10.1002/j.1939-4640.2004.tb02793.x.
[13] R. P. Amann and D. Waberski, "Computer-assisted sperm analysis (CASA): Capabilities and potential developments," *Theriogenology*, vol. 81, no. 1, pp. 5-17.e3, Jan. 2014, doi: 10.1016/j.theriogenology.2013.09.004.
[14] M. Yüzkat, H. O. Ilhan, and N. Aydin, "Multi-model CNN fusion for sperm morphology analysis," *Comput. Biol. Med*., vol. 137, p. 104790, Oct. 2021, doi: 10.1016/j.compbiomed.2021.104790.
[15] L. Spencer, J. Fernando, F. Akbaridoust, K. Ackermann, and R. Nosrati, "Ensembled Deep Learning for the Classification of Human Sperm Head Morphology," *Adv. Intell. Syst*., vol. 4, no. 10, p. 2200111, 2022, doi: 10.1002/aisy.202200111.
[16] H. Yang *et al*., "Multidimensional morphological analysis of live sperm based on multiple-target tracking," *Comput. Struct. Biotechnol. J*., vol. 24, pp. 176–184, Dec. 2024, doi: 10.1016/j.csbj.2024.02.025.
[17] M. E. Kandel *et al*., "Reproductive outcomes predicted by phase imaging with computational specificity of spermatozoon ultrastructure," *Proc. Natl. Acad. Sci*., vol. 117, no. 31, pp. 18302–18309, Aug. 2020, doi: 10.1073/pnas.2001754117.
[18] S. Javadi and S. A. Mirroshandel, "A novel deep learning method for automatic assessment of human sperm images," *Comput. Biol. Med*., vol. 109, pp. 182–194, Jun. 2019, doi: 10.1016/j.compbiomed.2019.04.030.
[19] J. Riordon, C. McCallum, and D. Sinton, "Deep learning for the classification of human sperm," *Comput. Biol. Med*., vol. 111, p. 103342, Aug. 2019, doi: 10.1016/j.compbiomed.2019.103342.
[20] R. G. Tiwari, A. Misra, and N. Ujjwal, "Image Embedding and Classification using Pre-Trained Deep Learning Architectures," in *2022 8th International Conference on Signal Processing and Communication (ICSC)*, Dec. 2022, pp. 125–130. doi: 10.1109/ICSC56524.2022.10009560.
[21] D. Kiela and L. Bottou, "Learning Image Embeddings using Convolutional Neural Networks for Improved Multi-Modal Semantics," in *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Doha, Qatar: Association for Computational Linguistics, 2014, pp. 36–45. doi: 10.3115/v1/D14-1005.
[22] J. Kim and Y. Kang, "Automatic Classification of Photos by Tourist Attractions Using Deep Learning Model and Image Feature Vector Clustering," *ISPRS Int. J. Geo-Inf*., vol. 11, no. 4, Art. no. 4, Apr. 2022, doi: 10.3390/ijgi11040245.
[23] Y. Gu, Y. Xu, X. Huang, J. Yang, W. Xue, and G.-Z. Yang, "Toward Robust Histology-Prior Embedding for Endomicroscopy Image Classification," *IEEE Trans. Med. Imaging*, vol. 41, no. 11, pp. 3242–3252, Nov. 2022, doi: 10.1109/TMI.2022.3180340.
[24] Y. Xu, W. Guo, Z. Zhang, and W. Yu, "Multiple Embeddings Contrastive Pretraining for Remote Sensing Image Classification," *IEEE Geosci. Remote Sens. Lett*., vol. 19, pp. 1–5, 2022, doi: 10.1109/LGRS.2022.3185729.
[25] Z. Ralte and I. Kar, *Learn Python Generative AI: Journey from autoencoders to transformers to*

large language models (English Edition). BPB Publications, 2024.
[26] Z. Hu, Q. Zhang, and M. He, *Advances in Artificial Systems for Logistics Engineering III*. Springer Nature, 2023.
[27] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size," Nov. 04, 2016, *arXiv*: arXiv:1602.07360. doi: 10.48550/arXiv.1602.07360.
[28] "GitHub - alyato/CNN-models-comparison: Comparison of famous convolutional neural network models," GitHub. Accessed: Oct. 03, 2024. [Online]. Available: https://github.com/alyato/CNN-models-comparison
[29] S. Salcedo-Sanz, J. L. Rojo-Álvarez, M. Martínez-Ramón, and G. Camps-Valls, "Support vector machines in engineering: an overview," *WIREs Data Min. Knowl. Discov.*, vol. 4, no. 3, pp. 234–267, 2014, doi: 10.1002/widm.1125.
[30] M. Awad and R. Khanna, "Support Vector Machines for Classification," in *Efficient Learning Machines: Theories, Concepts, and Applications for Engineers and System Designers*, M. Awad and R. Khanna, Eds., Berkeley, CA: Apress, 2015, pp. 39–66. doi: 10.1007/978-1-4302-5990-9_3.
[31] M. Pal, "Random forest classifier for remote sensing classification," *Int. J. Remote Sens.*, vol. 26, no. 1, pp. 217–222, Jan. 2005, doi: 10.1080/01431160412331269698.
[32] T. Hastie, R. Tibshirani, J. Friedman, T. Hastie, R. Tibshirani, and J. Friedman, "Random forests," *Elem. Stat. Learn. Data Min. Inference Predict.*, pp. 587–604, 2009.
[33] H. Kamel, D. Abdulah, and J. M. Al-Tuwaijari, "Cancer Classification Using Gaussian Naive Bayes Algorithm," in *2019 International Engineering Conference (IEC)*, Jun. 2019, pp. 165–170. doi: 10.1109/IEC47844.2019.8950650.
[34] S. Adinugroho and Y. A. Sari, *Implementasi Data Mining Menggunakan Weka*. Universitas Brawijaya Press, 2018.
[35] F. A. Breve, M. P. Ponti-Junior, and N. D. A. Mascarenhas, "Multilayer Perceptron Classifier Combination for Identification of Materials on Noisy Soil Science Multispectral Images," in *XX Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI 2007)*, Oct. 2007, pp. 239–244. doi: 10.1109/SIBGRAPI.2007.10.
[36] S. Yadav and S. Shukla, "Analysis of k-Fold Cross-Validation over Hold-Out Validation on Colossal Datasets for Quality Classification," in *2016 IEEE 6th International Conference on Advanced Computing (IACC)*, Feb. 2016, pp. 78–83. doi: 10.1109/IACC.2016.25.
[37] C. Sammut and G. I. Webb, *Encyclopedia of Machine Learning*. Springer Science & Business Media, 2011.
[38] H. O. Ilhan, I. O. Sigirci, G. Serbes, and N. Aydin, "A fully automated hybrid human sperm detection and classification system based on mobile-net and the performance comparison with conventional methods," *Med. Biol. Eng. Comput.*, vol. 58, no. 5, pp. 1047–1068, May 2020, doi: 10.1007/s11517-019-02101-y.
[39] J. Demšar *et al.*, "Orange: Data Mining Toolbox in Python," *J. Mach. Learn. Res.*, vol. 14, pp. 2349–2353, 2013.
[40] H. O. Ilhan, G. Serbes, and N. Aydin, "Automated sperm morphology analysis approach using a directional masking technique," *Comput. Biol. Med.*, vol. 122, p. 103845, Jul. 2020, doi: 10.1016/j.compbiomed.2020.103845.

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