



Separable CNN based Automated Classification of WBCs in Peripheral Blood Stream

Karthikeyan S^{1*}, Tathagat Banerjee², Sathya K³, Sumathi A C⁴

Abstract

The proportional percentage of each kind of white blood cell (WBC) in a blood sample is determined by blood cell classification, which is a popular diagnostic test. This test, on the other hand, is carried out by pathologists visually inspecting a blood sample, which is a time-consuming and difficult procedure. This test can also be done automatically with the right equipment. However, such equipment is costly and only available at major medical facilities. In this study, an alternate strategy for WBC detection and identification in a blood picture is provided, which is based on a low-cost microscope and digital camera combined with a separable convolutional neural network. The suggested method promises to generate 99.71 percent accuracy and 98.64 percent precision, respectively. It not only utilizes erratic optimizers and learning rate but also uses a large database of more than 10,000 samples.

Key Words: white blood cells; image segmentation; convolutional neural networks; classification; differential blood count

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1. Introduction

White blood cells (WBCs), red blood cells (RBCs), and platelets are the three types of blood cells. WBC are in charge of strengthening the immune system and combating foreign invaders. Their value has grown dramatically in periods when the epidemic is at full throttle. Each kind of WBC aids in the diagnosis of a variety of illnesses [1]. The existence of pernicious cancer is indicated by a high number of neutrophils in the blood. A large number of lymphocytes, on the other hand, implies AIDS, whereas a high number of monocytes and eosinophils indicates bacterial infection [1]. Because most of the country's laboratories are overburdened with samples and testing, the medical field is experiencing a severe labour shortage. Assistants who are very knowledgeable and talented in determining the number of different types of blood cells from the meniscus of samples. The process is not only time-consuming and tiresome, but it also places an unforeseen pressure on the lab personnel.

The approach intends to totally automate the identification and categorization of blood cells. In order to finish the work, it uses tiny pictures and samples. The model is far quicker than a typical human reaction, which can only scan 35 samples per hour at most. The model can validate 450 samples in under an hour and categorise them with a 99.86 percent accuracy.

2. Related Works

In order to assist the haematologists in detecting diseases like HIV-AIDS, leukaemia and blood cancer, computer science researchers developed blood cell semantic classification techniques. Sinha et al. used Bayesian classifiers to classify the WBS, and their accuracy was around 82.3% [1]. In a similar trend of probabilistic classifiers for this multiclass classification problem, Ghost et al. designed watershed algorithms to deduct 150 images and classify them [2]. Although unique, their accuracy tends to lie in the range of 83.2%.

Corresponding author: Karthikeyan S

Address: ^{1,4}Computer Science and Engineering, KPR Institute of Engineering and Technology, Coimbatore, Tamilnadu, India, ²Computer Science and Engineering, VIT-AP University, Andhra Pradesh, India, ³Computer Science and Engineering, Coimbatore



Institute of Technology, Coimbatore, Tamilnadu, India
E-mail:

skarathi.sns@gmail.com

Reza Tofighi et al. went further ahead and used the traditional artefacts of the Support vector machine and achieved an interesting 90% accuracy over 150 image samples [3].

Some work was done to classify different types of cells into each other using the handmade features of the model. The system used by SESSA to classify benign to malignant leukocytes by selecting useful traits from over 327 handmade traits [18]. Unfortunately, this approach still uses 224 features, making it difficult to describe and interpret the model. Moreover, not all of these features were self-interpretable and / or explainable. However, Lamberti built a model with interpretable and explainable capabilities that was superior to the various Convolutional Neural Networks (CNN) based approaches to classifying satellite images of ships and icebergs [19]. Therefore, we will use some of these features here as a guide to your model. Bikheth et al. achieved a 90.14% accuracy rate by using an entropy-based distance classifier [4]. G Liang developed a novel combination of CNN, Recurrent Neural Networks (RNN) based networks and achieved 90.79% classification Accuracy.

3. Proposed Methodology

Traditional machine learning techniques have not only shown to be hackneyed in this situation, but they also do not demonstrate their hegemony in the domain of computer vision and image analytics, as we have previously seen gasping via related publications. However, in this research, we will present a Convolution Neural Network-based architecture and compare it to the previous work. In order to attain the best accuracy, the study looks forward to using pre-trained models and weights as a reaction to quick neural network processing and combines multiple transfer learning techniques. The approach is broken down into several sections below.

3.1 Data

Identifying and categorising patient blood samples is a common part of diagnosing blood-based disorders. Methods for detecting and classifying blood cell subtypes that are automated have substantial medicinal applications [5][6]. The picture samples in the data set are divided into four categories: neutrophils, lymphocytes, monocytes, and eosinophils [7-10]. Figure 1 shows an example of the data that is available.

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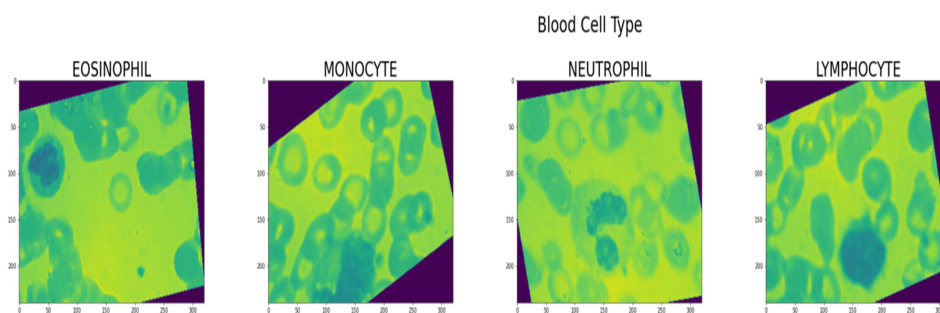


Fig. 1. Blood cell type

3.2 Capturing Data

To prevent any predetermined biases, the data contents of JPEG files must be examined properly and shuffled, as shown in the preceding segment. In order to look at the photographs, we also need to reduce the image size.

To address these issues, a 64-pixel width and height picture size is chosen after numerous trainings in order to imitate a minuscule frame size and optimally feed the supplied neural network [13-15]. Furthermore, we will stack all of the photos in grayscale in order to extract as many characteristics as feasible.

3.3 Model Structure

The model starts with a two-layered CNN [11, 12] structure, followed by a max-pooling layer. The input parameter is re-fed into the model. separable convolutional neural network for better feature extraction at each level.

3.4 Hyperparameter Tuning

Following the selection and consolidation of the model, we now attempt to extract the further optimization required in various parameters. For



the purposes of this work, the hyperparameters are treated as optimizers, with four alternative functions being considered: Adagrad, Adam, RMSprop Similarly, an extended consensus on the activation function choice is included. The author then manually fitted a number of different learning rates to find the optimal loss minimizer.

3.4.1 Optimizer Analytics

Table 1 demonstrates the best accuracies of RMSprop and Adam, 97.22% and 99.47%, respectively.

Table 1 : Optimizer Selection

Optimizer	DataSet	Accuracy	Precision	Recall	Sensitivity	Specificity
Adam	Train	99.47	97.56	95.48	98.75	97.42
	Valid	98.47	98.12	96.25	96.22	95.41
Adagrad	Train	74.15	75.6	71.42	75.48	75.98
	Valid	78.14	70.2	71.56	71.44	72.11
Rmsprop	Train	97.45	99.15	94.15	91.56	98.74
	Valid	97.22	99.98	94.59	95.56	94.25

(i) Activation Function Analytics

Table 2 showcases a quite similar trend in all types

of activation functions. Thus, for the use of this model, we shall stringently stick to Rectified Linear Units.

Table 2: Activation Function Selection

Dataset	Activation Function	Accuracy	Precision	Recall
Train	Selu	97	94	95
	Elu	95	95	94
	Softmax	96	94	98
	Tanh	87	88	85
	Relu	95	97	98
	SoftSign	78	72	87
	Sigmoid	84	88	88
Valid	Selu	95	94	92
	Elu	91	91	91
	Softmax	88	92	92
	Tanh	81	89	84
	Relu	96	96	98
	SoftSign	88	87	81
	Sigmoid	88	84	80



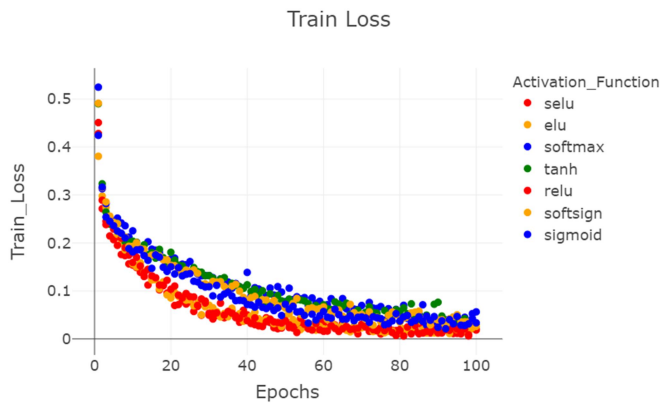


Fig. 2. Training Loss Activation Function

(ii) Transfer Learning [10] Models

As elaborated earlier, the paper proposes to incorporate pre-trained models as a substantive propitious option to the persisting models. To do the same, the paper uses a very simple architectural

use of the VGG16 and Inception model (Table 3). The results stand relatively taller than any of the other models and can be witnessed in the next section.

Table 3: Model Comparison with state of the art

Model	Dataset	Accuracy	Precision	Recall	Specificity
VGG	Train	77	74	79	74
	Valid	71	75	75	76
DENSENE T 152	Train	88	89	88	84
	Valid	85	81	86	86
Google NET	Train	92	95	97	97
	Valid	95	97	92	95
HYBRID	Train	99	98	99	97
	Valid	95	96	93	91

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4. Results

As previously stated, we will be utilising Adam and relu with a learning rate of 0.00002548 for our model. The final findings of our model are shown in Figure 9.

percent train precision. Its accuracy in real-world applied test data is 93 percent, in addition to its outstanding training performance. Figure 3 shows more class-by-class categorization and other statistical data.

It's also worth pointing out that the final model 0.026 train loss, 99.68 percent train accuracy, 98.57

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Classes : ['EOSINOPHIL' 'LYMPHOCYTE' 'MONOCYTE' 'NEUTROPHIL']
precision recall f1-score support
EOSINOPHIL    0.80    0.99    0.88    310
LYMPHOCYTE    1.00    0.99    1.00    319
MONOCYTE      1.00    0.98    0.99    328
NEUTROPHIL    0.98    0.76    0.86    295

accuracy                    0.93    1252
macro avg    0.94    0.93    0.93    1252
weighted avg 0.95    0.93    0.93    1252
    
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Fig. 3. Class wise Result



Finally, after comparing all of the statistical parameters and graphs, it's only fair to see the suggested model's actual outcomes. Figure 10 shows the same concept in an actual vs. expected labelling format. Also, an important point to consider and highlight is that all the transfer learning [16-17] algorithms also have done exceptionally well, achieving an accuracy of 77.54% and 92.8% for the VGG16 and Inception model, but still, our proposed architecture has resonated with an accuracy of more than 99.5% for the given blood-cells dataset [6]. Basophil vs Eosinophil vs

Lymphocyte vs Monocyte vs Neutrophil Mononuclear (Basophil + Lymphocyte vs Monocyte) vs Polynuclear (Neutrophil + Eosinophil) An important problem in blood diagnostics is classifying different types of blood cells. Here we have 410 original images and 12,500 augmented images of blood cells paired with subtype labels (Basophil vs Eosinophil vs Lymphocyte vs Monocyte vs Neutrophil). We want to automatically classify each image according to the subtype of cells within it

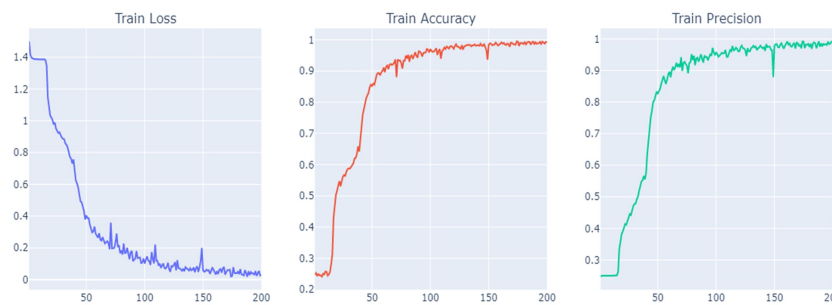


Fig. 4. Hybrid Model Results

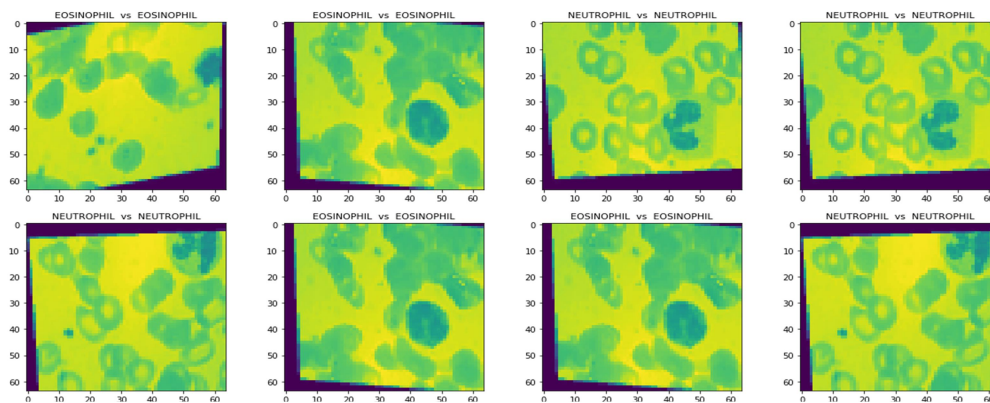


Fig. 5. Result Images

5. Conclusion

The article not only achieved a higher and closer to 100 percent accuracy than [6], but it also outperformed the well-known transfer learning algorithms VGG16 and Inception model. Beyond that, the model provides a portal of wisdom and hegemony. As previously said, the medical field's core requirement is automated categorization of various pictures and materials obtained. Thus, its route clears industrial application to help society in times of pandemic with significantly greater precision than its predecessors. Even after obtaining near-perfect accuracy, our models should evolve as medical research does. The future

potential rests in not only categorising the image into a certain category, but also binding and duplicating the contour for further categorization and analysis. However, robust data collecting and communication between the medical and computational industries will be required.

Declarations

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Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

Not applicable

Code availability

Not applicable

Author contributions

The corresponding author claims the major contribution of the paper including formulation, analysis and editing. The Co-authors provide guidance to verify the analysis result and manuscript editing.

References

- Sinha, N., & Ramakrishnan, A. G. (2003, October). Automation of differential blood count. In TENCON 2003. Conference on Convergent Technologies for Asia-Pacific Region (Vol. 2, pp. 547-551). IEEE. DOI: 10.1109/TENCON.2003.1273221.
- Ghosh, M., Das, D., Mandal, S., Chakraborty, C., Pala, M., Maity, A. K., ... & Ray, A. K. (2010, April). Statistical pattern analysis of white blood cell nuclei morphometry. In 2010 IEEE Students Technology Symposium (TechSym) (pp. 59-66). IEEE. DOI: 10.1109/TECHSYM.2010.5469197.
- Reza Tofighi, S. H., & Soltanian-Zadeh, H. (2011). Automatic recognition of five types of white blood cells in peripheral blood. *Computerized Medical Imaging and Graphics*, 35(4), 333-343.
- Bikhet, S. F., Darwish, A. M., Tolba, H. A., & Shaheen, S. I. (2000, June). Segmentation and classification of white blood cells. In 2000 IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings (Cat. No. 00CH37100) (Vol. 4, pp. 2259-2261). IEEE.
- Banerjee, T., Karthikeyan, S., Sharma, A., Charvi, K. and Raman, S. (2022). Attention-Based Discrimination of Mycoplasma Pneumonia. *Proceedings of International Conference on Computational Intelligence and Data Engineering*, pp.29-41. doi:10.1007/978-981-16-7182-1_3.
- Young, I. T. (1972). The classification of white blood cells. *IEEE Transactions on Biomedical Engineering*, (4), 291-298.
- Liang, G., Hong, H., Xie, W., & Zheng, L. (2018). Combining convolutional neural network with recursive neural network for blood cell image classification. *IEEE access*, 6, 36188-36197.
- Pang, S., Du, A., Orgun, M. A., & Yu, Z. (2019). A novel fused convolutional neural network for biomedical image classification. *Medical & biological engineering & computing*, 57(1), 107-121.
- Urtnasan, E., Park, J. U., & Lee, K. J. (2018). Multiclass classification of obstructive sleep apnea/hypopnea based on a convolutional neural network from a single-lead electrocardiogram. *Physiological measurement*, 39(6), 065003.
- Banerjee, T., Jain, A., Sethuraman, S. C., Satapathy, S. C., Karthikeyan, S., & Jubilson, A. (2021). Deep Convolutional Neural Network (Falcon) and transfer learning-based approach to detect malarial parasite. *Multimedia Tools and Applications*, 1-15. DOI: 10.1007/s11042-021-10946-5
- Banerjee, T., Batta, D., Jain, A., Karthikeyan, S., Mehndiratta, H., & Hari Kishan, K. (2021). Deep belief Convolutional Neural Network with Artificial Image Creation by GANs Based Diagnosis of Pneumonia in Radiological Samples of the Pectoralis Major. In *Innovations in Electrical and Electronic Engineering* (pp. 979-1002). Springer, Singapore.
- Karthikeyan, S., Seetha, H., Manimegalai, R "An efficient toilet queue based scheduling model for deadline based jobs in multi-node hadoop clusters(2019)", *Journal of Advanced Research in Dynamical and Control Systems*, 11 (6 Special Issue), pp. 647-655.
- Rajyaguru, V., Vithalani, C., & Thanki, R. (2020). A literature review: various learning techniques and its applications for eye disease identification using retinal images. *International Journal of Information Technology*, 1-12. DOI: 10.1007/s41870-020-00442-8
- Kanaparthi, S. K., & Raju, U. S. N. (2022). Content based image retrieval on big image data using local and global features. *International Journal of Information Technology*, 14(1), 49-68. DOI: 10.1007/s41870-021-00806-8
- Jiranyakul, P., & Yoksvad, C. (2011). Consumer attitudes toward Quick Service Restaurants in Thailand: the study of influencing factors affecting purchase making decision.
- Kim, W. G., & Kim, H. B. (2004). Measuring customer-based restaurant brand equity. *Cornell hotel and restaurant administration Quarterly*, 45(2), 115-131.
- Kuo, Y. F., & Hou, J. R. (2017). Oppositional brand loyalty in online brand communities: perspectives on social identity theory and consumer-brand relationship. *Journal of Electronic Commerce Research*, 18(3), 254.
- A.T. Sahlol, A.M. Abdeldaim, A.E. Hassanien Automatic acute lymphoblastic leukemia classification model using social spider optimization algorithm *Soft comput*, 23 (15) (2019), pp. 6345-6360, 10.1007/s00500-018-3288-5
- W.F. Lamberti Classification of Synthetic Aperture Radar Images of Icebergs and Ships Using Random Forests Outperforms Convolutional Neural Networks 2020 IEEE Radar Conference (RadarConf20) (2020), pp. 1-6.

