International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 20 No. 2 (2024)



ijerst.editor@gmail.com

editor@ijerst.com

International Journal of Engineering Research and Science & Technology

ISSN 2319-5991 www.ijerst.com
Vol. 20, No. 2, 2024
© 2024 IJERST. All Rights Reserved

Research Paper

ENHANCED DEEP CNN FOR PRECISE MULTICLASS CLASSIFICATION OF BLOOD CELL SUBTYPES IN HISTOLOGICAL IMAGES

Madhavi Pingili[1], Suthari Vamshi[2], Sallagolusula Venkata Sudheshna[2], Cheekoti Sushmasri[2], Inapanuri Vivek Kumar [2]

[1]Assistant Professor, [2]UG Student, [1,2] Department of Information Technology

[1,2]CMR Engineering College (UGC-Autonomous), Medchal Rd, Kandlakoya, Telangana 501401

Received: 07-3-2024 Accepted: 12-4-2024 Published: 22-4-2024

ABSTRACT

White blood cells (WBCs), or leukocytes, are a crucial component of the immune system, responsible for defending the body against infections through mechanisms such as pathogen ingestion, antibody production, and direct destruction of infectious agents. Leukocytes are classified into five major subtypes: neutrophils, eosinophils, lymphocytes, monocytes, and basophils. Accurate identification and quantification of these subtypes play a vital role in clinical diagnosis, aiding in the detection of infections, immune disorders, and the monitoring of cancer treatments. Traditional manual differentiation of WBCs under a microscope is labor-intensive, time-consuming, and prone to errors, highlighting the need for automated classification techniques.Conventional machine learning-based classification methods rely on handcrafted features and often involve multiple steps, including preprocessing, segmentation, feature extraction, and classification, which may compromise accuracy and efficiency. In contrast, deep learning, particularly convolutional neural networks (CNNs), has revolutionized image-based classification by enabling end-to-end learning from raw images. This study presents an Enhanced Deep CNN for precise and automated multiclass classification of blood cell subtypes from histological images. The proposed approach leverages advanced CNN architectures to learn hierarchical feature representations, improving classification accuracy and robustness. By eliminating the dependency on manual feature selection, this model enhances diagnostic efficiency, offering a powerful tool for hematologists and medical practitioners in WBC analysis.

KEYWORDS : White Blood Cells (WBCs), Leukocytes, Blood Cell Classification, Histological Image Analysis, Multiclass Classification.

1. INTRODUCTION

Blood is a specialized body fluid. Its main components are red blood cells, plasma, platelets, and white blood cells. WBCs protect the body from infections, accounting for about 1% of human blood [1]. Basophils, Eosinophils, Lymphocytes, Monocytes, and Neutrophils are the types of white blood cells, Basophils white blood cells accounting only around 1%, they are important in mounting a nonspecific immune response to pathogens. Eosinophils play an important role in fighting bacteria and responding to infections with parasites. Lymphocytes are also very important in the immune system, they are 2 types: B and T lymphocytes, with B cells producing antibodies, T cells being responsible for directly killing many foreign invaders. Monocytes are responsible for cleaning up dead cells. Roughly half of the white blood cells are Neutrophils; they are usually the first cells of the immune system to respond to an

invader such as a bacterium or a virus [2]. White blood cells (WBCs) classification is an important step because it can assist hematologists in the diagnosis of several blood disorders, such as leukemia, some immunological disorders, and certain types of cancer. The analysis procedure can be done by automatic and manual approaches to count and classify WBC. The manual classification of WBC has many medical difficulties, including error in the accuracy of results due to sampling errors and statistical probabilities and poor sensitivity, specificity, and predictive values. Furthermore, some automatic approaches in the laboratories have used instruments, such as flow cytometry and automatic counting machine to detect and classify WBC. These instruments do not make use of image processing techniques, and they can count and classify WBCs quantitatively not qualitatively. Therefore, it is necessary to design an automatic system which includes computer-based systems for classification of WBCs.

Researchers are increasingly interested in the development of algorithms for automated analysis of medical images such as microscopic blood smear images. They are using different correlated techniques like; image processing, computer vision, artificial neural networks, machine learning algorithms, etc. [3]. To overcome all these problems, we added the help of CNN to image processing. In this framework, we present a RBC image analysis with the convolution neural network (CNN). CNN is a strong image classifer tool, in which image is taken as input, classify it under certain categories based on their features. In CNN, an individual unit is called a neuron. Neurons are in a series of layers. Neurons of one layer are connected to the neurons of the next layer. Each neuron or node of one layer perform mathematical calculation and pass the results to the next node. The last layer of the neural network has increased computational power due to the accumulation of experience.

2. LITERATURE SURVEY

Alzubaidi et al. [4] introduced a new robust and effective deep Convolutional Neural Network to classify Red Blood Cells (RBCs) in three classes namely: normal (‘N’) abnormal (sickle cells anemia type (‘S’)) and miscellaneous (‘M’). To improve the results further, we have used this model as features extractor then this work applied an error-correcting output codes (ECOC) classifier for the classification task. This model with ECOC showed outstanding performance and high accuracy of 92.06%.

Rahman et al. [5] experimented the existing standard pre-processing techniques from the literature. In addition, several other complex architectures have been implemented and tested to pick the best performing model. A holdout test has also been conducted to verify how well the proposed model generalizes on unseen data. This best model achieved an accuracy of almost 97.77%.

Roopa et al. [6] demonstrated classification of white blood cells into six types namely lymphocytes, monocytes, neutrophils, eosinophils, basophils and abnormal cells. This work provided the comparison of traditional image processing approach and deep learning methods for classification of white blood cells. This work also evaluated neural network classifier results for hand-crafted features and obtained the average accuracy of 99.8%. And used full training and transfer learning approaches of convolutional neural network for the classification. An accuracy around 99% was obtained for full training CNN.

Malkawi et al. [7] classified the microscopic WBCs images using a hybrid system where Convolutional Neural Network (CNN) used as features extractor and different machine learning algorithms used as classifiers, then the performances of these classifiers were evaluated to recognize the best of them. These algorithms included Support Vector Machine (SVM), k-Nearest Neighbor (KNN) and Random Forest, for training and test parameters this framework used five features that were extracted from the images.

According to results of performance, the RF performed better than the other methods with a testing accuracy reached 98.7%.

Matek et al. [8] compiled an annotated image dataset of over 18,000 white blood cells, use it to train a convolutional neural network for leukocyte classification and evaluate the network's performance by comparing to inter- and intra-expert variability. The network classified the most important cell types with high accuracy. It also allows us to decide two clinically relevant questions with human-level performance: (1) if a given cell has blast character and (2) if it belongs to the cell types normally present in non-pathological blood smears. This framework approach holds the potential to be used as a classification aid for examining much larger numbers of cells in a smear than can usually be done by a human expert. This will allow clinicians to recognize malignant cell populations with lower prevalence at an earlier stage of the disease.

Sadafi et al. [9] presented an active learning framework that identifies the most relevant samples from a large set of not annotated data for further expert annotation. Applied to brightfield images of red blood cells with seven subtypes, this work trained a faster R-CNN for single cell identification and classification, calculate a novel confidence score using dropout variational inference and select relevant images for annotation based on (i) the confidence of the single cell detection and (ii) the rareness of the classes contained in the image. This framework showed that this approach leads to a drastic increase of prediction accuracy with already few annotated images. This original approach improves classification of red blood cell subtypes and speeds up the annotation. This important step in diagnosing blood diseases will profit from our framework as well as many other clinical challenges that suffer from the lack of annotated training data.

Parab et al. [10] utilized the algorithm which can extract the feature of each segmented cell image and classify it into 9 various types. Images of blood slides were collected from the hospital. The overall accuracy was 98.5%. The system has been developed to provide accurate and fast results that can save patients' lives.

Paravil et al. [11] tried to devise a methodology for automation by using feature fusion. For feature extraction, various fusion techniques using transfer-learning approaches such as Densely connected convoluted neural networks (DenseNet201) and VGG16 (Visual Geometry Group 2016) were proposed. The classification results are compared using various performance metrics such as Accuracy, Precision, Recall, and F1-Score. The maximum accuracy of 89.75% was obtained with the help of feature fusion combined with the Convolutional Neural Network (CNN) classifier.

Yildirim et al. [12] proposed one of the most popular neural networks, convolutional neural network (CNN) is selected to differentiate between different types of white blood cells, namely, eosinophil, lymphocyte, monocyte and neutrophil. The CNN was coupled with Alexnet, Resnet50, Densenet201 and GoogleNet in turn, and trained with the Kaggle Dataset. Then, Gaussian, and median filters were applied separately to the images in the database. The new images were classified again by the CNN with each of the four networks. The results obtained after applying the two filters to the images were better than the results obtained with the original data. The research results make it easier to diagnose blood related diseases.

3. PROPOSED SYSTEM

The "Deep CNN for Multiclass Classification of Subtype Blood Cells from Histological Images" project aims to develop a sophisticated deep learning model to accurately classify different types of white blood cells (WBCs) from histological images. The project utilizes convolutional neural networks (CNNs), a powerful class of deep learning algorithms well-suited for image classification tasks.

The main objectives of the project include:

1. **Data Acquisition and Preprocessing**: The project involves acquiring a dataset

consisting of histological images of white blood cells, representing various subtypes. These images are preprocessed to ensure uniformity in size and format, making them suitable for input into the deep learning model.

2. **Model Training**: The core of the project involves training a deep CNN model using the preprocessed histological images. The CNN architecture consists of multiple convolutional layers followed by pooling layers for feature extraction, along with fully connected layers for classification. The model is trained using a subset of the dataset for learning and optimization.
3. **Evaluation and Performance Analysis**: Once trained, the model is evaluated using a separate subset of the dataset to assess its classification performance. Metrics such as accuracy, precision, recall, and F1 score are calculated to measure the model's effectiveness in correctly identifying different WBC subtypes.
4. **Deployment and Classification**: The trained CNN model is then deployed for practical use, where it can classify WBCs from new histological images. Users can input an image containing white blood cells, and the model will predict the subtype of each cell based on learned patterns from the training data.

The project is a user-friendly interface for uploading datasets, preprocessing images, training the CNN model, and performing classification tasks. Additionally, it offers functionalities for visualizing performance metrics and evaluating the effectiveness of the trained model.

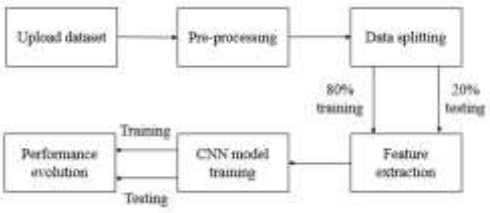


Figure 1: Block diagram of proposed system.

4. RESULTS AND DISCUSSION

The figure below depicts the graphical user interface (GUI) for a WBC (White Blood Cell) classification system using histogram images. It has features and options for users to interact with the application for classifying WBCs.



Figure 2: Displays the GUI interface for the classification of WBC from Histogram Images.

This figure 2 shows the GUI interface where users can upload a dataset for the classification task. The dataset contains histogram images of WBCs for training and testing the classification model.



Figure 3: Represents the upload of Dataset using GUI.

The figure 4 illustrates the loaded dataset along with its corresponding class labels. It provides an overview of the data, helping users understand the distribution of different classes in the dataset.



Figure 4: Displays the loaded dataset and its class labels.

The figure 5 presents a visualization of both the loaded training and testing images. It help to inspect and understand the images that the

classification model will be trained on and tested against.



Figure 5: Displays the both loaded train and test images.

The figure 6 has both confusion matrix and a Receiver Operating Characteristic (ROC) curve for the Decision Tree model. The confusion matrix provides insights into the model's classification performance, and the ROC curve illustrates its trade-offs between true positive rate and false positive rate.

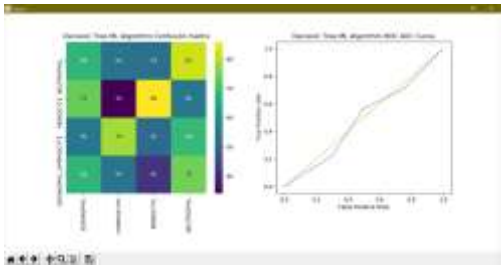


Figure 6: Presents the confusion and ROC graph for Decision Tree model.

The figure below provides the evaluation metrics for a Convolutional Neural Network (CNN) applied to the WBC classification task.

The figure 7 has both a confusion matrix and an ROC curve for the CNN model. It used to compare the performance of the CNN model with the Decision Tree model.

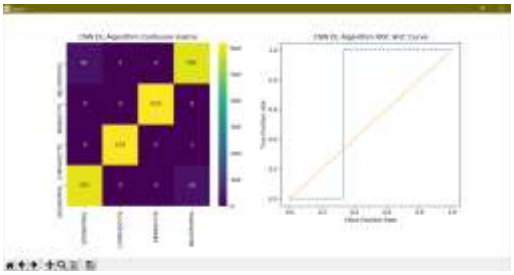


Figure 7: Presents the confusion and ROC graph for CNN model.

The figure 8 shows the GUI interface where users can upload test WBC images for the model to make predictions. It is a step in the evaluation process.

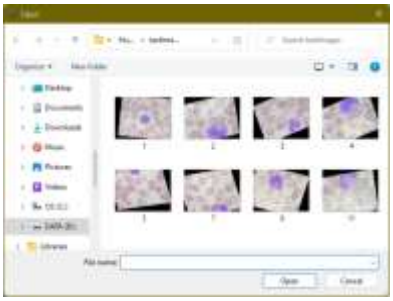


Figure 8: Represents the upload test WBC images.

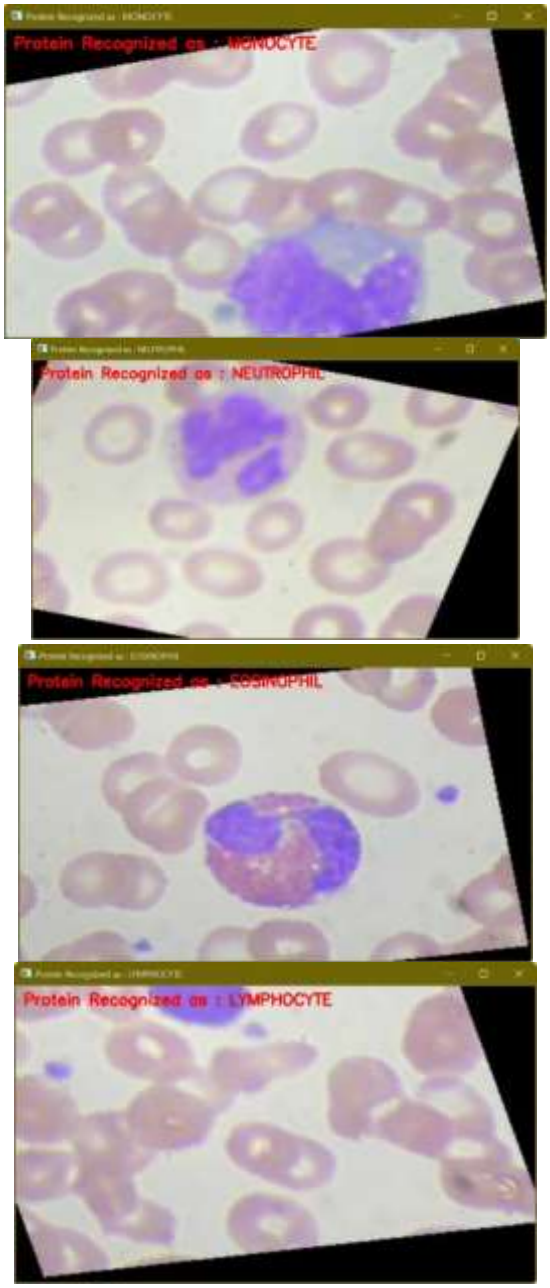


Figure 9: Shows the model predicated test images as monocyte, neutrophil etc..

5. CONCLUSION

This project successfully tackled the challenge of automatically classifying white blood cells (WBCs) from histological images using deep convolutional neural networks (CNNs). By leveraging the power of deep learning, the proposed approach enables precise and efficient identification of different WBC subtypes, significantly enhancing the accuracy and reliability of blood cell analysis. The automation of this process holds great clinical significance, as it streamlines diagnostic workflows and facilitates the early detection of abnormalities, ultimately improving patient care.Unlike traditional methods that rely on manual feature engineering, the CNN-based approach learns hierarchical representations directly from raw histological images, eliminating the need for handcrafted features. This not only enhances classification accuracy but also reduces the time and effort required for analysis, making it a valuable tool for hematologists and medical professionals. The success of this project highlights the transformative potential of artificial intelligence in healthcare, paving the way for more advanced and efficient diagnostic solutions in medical imaging.

REFERENCES

[1] C. Shorten and T. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning", Journal of Big Data, vol. 6, no. 1, 2019. Available: 10.1186/s40537-019-0197-0.

[2] "The American Society of Hematology", Hematology.org, 2020. [Online]. Available: https://www.hematology.org. [Accessed: 28- Nov- 2019].

[3] AL-Dulaimi, Khamael, et al. "Classification of white blood cell types from microscope images: Techniques and challenges." Microscopy Science: Last Approaches on Educational Programs and Applied Research. Vol. 8. Formatex Research Center, 2018.

[4] Alzubaidi, L., Al-Shamma, O., Fadhel, M.A., Farhan, L., Zhang, J. (2020). Classification of Red Blood Cells in Sickle Cell Anemia Using Deep Convolutional Neural Network. In: Abraham, A., Cherukuri, A., Melin, P., Gandhi, N. (eds) Intelligent Systems Design and Applications. ISDA 2018 2018. Advances in Intelligent Systems and Computing, vol 940. Springer, Cham. https://doi.org/10.1007/978-3-030-16657-1_51.

[5] Rahman, A., Zunair, H., Rahman, M. S., Yuki, J. Q., Biswas, S., Alam, M. A., ... & Mahdy, M. R. C. (2019). Improving malaria parasite detection from red blood cell using deep convolutional neural networks. arXiv preprint arXiv:1907.10418.

[6] Roopa B. Hegde, Keerthana Prasad, Harishchandra Hebbar, Brij Mohan Kumar Singh, Comparison of traditional image processing and deep learning approaches for classification of white blood cells in peripheral blood smear images, Biocybernetics and Biomedical Engineering, Volume 39, Issue 2, 2019, Pages 382-392, ISSN 0208-5216, https://doi.org/10.1016/j.bbe.2019.01.005.

[7] A. Malkawi, R. Al-Assi, T. Salameh, B. Sheyab, H. Alquran and A. M. Alqudah, "White Blood Cells Classification Using Convolutional Neural Network Hybrid System," 2020 IEEE 5th Middle East and Africa Conference on Biomedical Engineering (MECBME), 2020, pp. 1-5, doi: 10.1109/MECBME47393.2020.9265154.

[8] Matek, C., Schwarz, S., Spiekermann, K. et al. Human-level recognition of blast cells in acute myeloid leukaemia with convolutional neural networks. Nat Mach Intell 1, 538–544 (2019). https://doi.org/10.1038/s42256-019-0101-9

[9] Sadafi, A. et al. (2019). Multiclass Deep Active Learning for Detecting Red Blood Cell Subtypes in Brightfield Microscopy. In: , et al. Medical Image Computing and Computer Assisted Intervention – MICCAI 2019. MICCAI 2019. Lecture Notes in Computer Science(), vol 11764.

Springer, Cham. https://doi.org/10.1007/978-3-030-32239-7_76.

[10] Parab, M.A., Mehendale, N.D. Red Blood Cell Classification Using Image Processing and CNN. SN COMPUT. SCI. 2, 70 (2021). https://doi.org/10.1007/s42979-021-00458-2.

[11] S. Parayil and J. Aravinth, "Transfer Learning-based Feature Fusion of White Blood Cell Image Classification," 2022 7th International Conference on Communication and Electronics Systems (ICCES), 2022, pp. 1468-1474, doi: 10.1109/ICCES54183.2022.9835815.

[12] Yildirim, Muhammed & Çinar, Ahmet. (2019). Classification of White Blood Cells by Deep Learning Methods for Diagnosing Disease. Revue d'Intelligence Artificielle. 33. 335-340. 10.18280/ria.330502.