White Blood Cells Detection by Using Convolutional Neural Network (CNN)

Mrs. K.Amutha, M.E.[1],
"Department of Computer Science and "Engineering, Bharath Institute of Higher "Education and Research, "Chennai, India
"amutha.cse@gmail.com[1.]

S.Sabeer khan[2],
Department of Computer Science and Engineering,Bharat Institute ofHigherEducation and research,Chennai,India.
sabeersabee20@gmail.com[2] .

S.Akhil Kumar[3],
Department of Computer Science and Engineering,Bharat Institute of Higher Education and research,Chennai,India.
kumarnaidu753@gmail.com[3]

P. Madhavan[4],
Department of Computer Science and Engineering,Bharat Institute of Higher Education and research,Chennai,India.
Chinnumadhavan0@gmail.com[4].

B. Sriram[5]
Department of Computer Science and Engineering,Bharat Institute of Higher"Education and research,Chennai,India".
Srirambandi851@gmail.com.

Abstract: The microscopic examination of blood smears is a vital diagnostic tool for assessing patients' health. This technique involves utilizing a microscope to manually count the percentage of each cell type within a designated area of interest on smears. However, this manual process is both laborious and time-consuming, with accuracy reliant on the expertise of the operators. Consequently, the imperative for an automated differential counting system has become evident. In this initiative, Convolutional Neural Network (CNN) models play a pivotal role. To attain optimal performance from deep learning methods, extensive training data is essential. For our project, we utilized images of white blood cells during the training phase, leading to a significant enhancement in accuracy compared to traditional methods. The application of CNNs allowed us to generate results within seconds, addressing the limitations of manual counting. White blood cells, constituting only approximately 1% of the blood, wield a substantial impact on immunity. Referred to as leukocytes, they tirelessly combat pathogens circulating in the bloodstream, safeguarding against illnesses. The bone marrow continuously produces white blood cells, particularly short-lived neutrophils, ensuring a constant supply. Our proposed CNN-based approach strives to automate white blood cell classification, leveraging deep learning to augment accuracy and efficiency. The model undergoes training on a diverse dataset, enabling it to discern intricate features and patterns associated with different cell types. Notably, the model demonstrates not only high classification accuracy but also resilience to variations in cell morphology and staining techniques. This research significantly contributes to the ongoing utilization of deep learning in medical image analysis, specifically within hematology. The automated classification of white blood cells through CNNs holds great promise for enhancing diagnostic processes, benefiting both healthcare professionals and patients.

Keywords: CNN, efficiency, hematology.

I. INTRODUCTION

WBCs, sometimes referred to as leukocytes or leucocytes, are essential for defending the body against infections and foreign invaders. These cells, which come from hematopoietic cells in the bone marrow, are found in the blood and lymphatic systems and are spread throughout the body. White blood cells are differentiated from anucleated red blood cells (RBCs) and platelets in the blood composition by their nuclei.

Comprising a mere 1% of the blood, white blood cells exert a significant influence on immune defense. Functioning as immunity cells, they perpetually combat viruses, bacteria, and other threats circulating in the bloodstream. In times of bodily distress, white blood cells swiftly converge on affected areas to neutralize harmful substances, thereby preventing illness.

The bone marrow serves as the production site for white blood cells, which are subsequently stored in blood and lymph tissues. Given the short lifespan of certain white blood cells, particularly neutrophils, lasting less than a day, continuous production occurs in the bone marrow. This project's primary objective is to construct a deep learning model utilizing CNNs for the categorization of white blood cells into distinct subtypes.

The model's training will involve a labeled dataset of blood cell images, enabling it to identify patterns and features specific to different white blood cell types. The ultimate goal is to establish an automated system that aids medical professionals in diagnosing diseases based on blood cell morphology.

The project encompasses several key stages:

Data Collection: Curate a diverse and well-labeled dataset featuring images of white blood cells, including neutrophils, lymphocytes, monocytes, eosinophils, and basophils.

Data Preprocessing: Normalize and augment the dataset to enhance the model's generalization capabilities. This involves resizing, cropping, and introducing variations to the images.

CNN Architecture Design: Develop a CNN architecture suitable for image classification. Experiment with various layers, filter sizes, and activation functions to optimize performance.

Model Training: Employ a suitable optimization algorithm to train the CNN on the prepared dataset. Monitor performance on validation data to prevent overfitting.

Model Evaluation: Assess the model on a separate test dataset, determining accuracy, precision, recall, and F1-score for each white blood cell subtype.

Model Refinement: Refine the model based on evaluation results to enhance performance and generalization capabilities.

The envisioned outcome is a proficiently trained CNN model capable of accurately classifying white blood cells into distinct subtypes. This innovation promises enhanced efficiency in diagnosing diseases linked to abnormalities in white blood cell counts, reducing manual effort and potential human error inherent in traditional blood cell classification methods. The automation of white blood cell classification through deep learning has the potential to revolutionize medical diagnostics, facilitating rapid and precise identification of white blood cell subtypes for early disease detection and timely intervention, thereby improving overall patient outcomes.

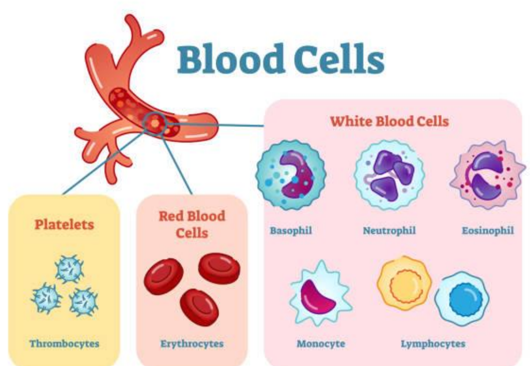

Fig.1 Blood cells

II. LITERATURE SURVEY

Rosyadi et al. undertook pioneering research in the realm of White Blood Cell (WBC) classification, delving into the analysis of blood cell images acquired through digital microscopes examining blood smear samples. The methodology hinged on the utilization of the Otsu threshold method for segmentation and the application of the K-Means clustering technique for classification. A crucial discovery emerged, emphasizing the paramount importance of circularity geometry features when implementing k-means clustering for WBC categorization, resulting in an accuracy rate of 67%.

In a distinct investigation, Gautam et al. introduced an inventive approach by integrating the Naïve Bayes classifier with morphological features to distinguish WBC. The encompassed features in their training system included area, eccentricity, perimeter, and circularity. Impressively, this novel method achieved a remarkable accuracy rate of 80.88%.

Contributing to the advancement of WBC classification, Yu et al. proposed a methodology harnessing Convolutional Neural Networks (CNN). Employing various network architectures such as ResNet50, Inception V3, VGG 16, VGG 19, and Xception, this innovative approach exhibited notable efficiency, yielding an accuracy rate of 88.5%.

In the research paper titled "Dermatologist-level classification of skin cancer with deep neural networks," the authors detail the comprehensive training of a singular CNN using images to classify skin lesions. The CNN underwent training and evaluation with 129,450 clinical images representing 2,032 distinct diseases. Results showcased the CNN's performance on par with board-certified dermatologists, validating the capacity of artificial intelligence in skin cancer classification at a professional level.

Furthermore, a CNN-based method for leukocyte classification featuring multiscale feature extraction demonstrated effectiveness in detecting blood cells, as highlighted in the study titled "Leukocyte Classification Using Convolutional Neural Network with Multiscale Feature Extraction." Another article, "Automated White Blood Cell Classification Using Deep Convolutional Neural Networks," presented an automated CNN-based white blood cell classification system, yielding promising subtype identification results.

The paper titled "Automated White Blood Cell Classification through Pre-trained Deep Learning Models: ResNet and Inception" delves into computer-aided diagnosis for efficient WBC classification. The study advocates the automation of manual diagnosis through a three-step pre-processing method and the utilization of Inception and ResNet architectures. Results indicate significant success, with the framework achieving a 100% accuracy rate in detecting the four main WBC types using ResNet V1 50. Alternative outcomes include accuracy rates of 99.84% and 99.46% with ResNet V1 152 and ResNet 101, respectively, after 3000 epochs and fine-tuning all layers.

III. RELATED WORKS

Existing System:

The current system employs traditional machine learning algorithms for the classification of blood cell types based on dataset information. White blood cell analysis relies on manual methods, introducing labor-intensive and time-consuming processes. Algorithms such as K-means Clustering and Random Forest Techniques are utilized, but challenges include limited throughput, dependency on human expertise, and difficulties handling large datasets.

Advantages of the Existing System:

Familiarity with Traditional Algorithms: Traditional ML algorithms like K-means Clustering and Random Forest Techniques are well-established in the medical field.

Manual Expertise: Human involvement allows nuanced analysis and interpretation by skilled medical professionals.

Established Processes: Manual examination of blood smears is a widely accepted practice in healthcare settings.

Initial Implementation Costs: Traditional algorithms may have lower resource requirements initially.

Disadvantages of the Existing System:

Algorithmic Improvement Needed: The accuracy of the algorithm could be enhanced with more advanced techniques.

Limited Image Processing Rate: The existing system's image processing rate is suboptimal and can be improved.

Resource Intensiveness: Manual methods demand significant resources, leading to challenges in resource-limited healthcare settings.

Proposed System:

To address the limitations inherent in the existing system, the proposed solution introduces a novel CNN-based Deep Learning Algorithm designed for the categorization of white blood cells. By employing scaled and preprocessed images during training, the algorithm demonstrates a commendable accuracy rate of approximately 96%. This CNN methodology streamlines the identification and classification of white blood cells, substantially diminishing the necessity for manual scrutiny.

Advantages of the Proposed System:

Automation and Efficiency: Automated processing reduces reliance on manual inspection, expediting white blood cell analysis.

Accuracy and Consistency: CNNs improve accuracy by learning intricate features, minimizing subjectivity and inconsistencies.

High Throughput: The proposed system processes a large number of images rapidly, facilitating timely diagnoses.

Reduced Dependence on Human Expertise: Minimized reliance on human expertise reduces the risk of errors and ensures consistent performance.

Purpose of the System:

The main purpose is to revolutionize white blood cell analysis through automated CNN integration. The proposed system aims for efficiency, accuracy, and scalability, reducing labor-intensive processes and subjectivity. It leverages technology to advance hematology, offering an innovative tool for improved diagnostic outcomes.

The system also focuses on building a machine learning model for white blood cell type detection, particularly emphasizing fine-grained differences in skin lesions. Utilizing convolutional neural networks, the system extracts features through machine learning, aligning with the project's commitment to innovation in hematology diagnostics.

IV. METHODOLOGY

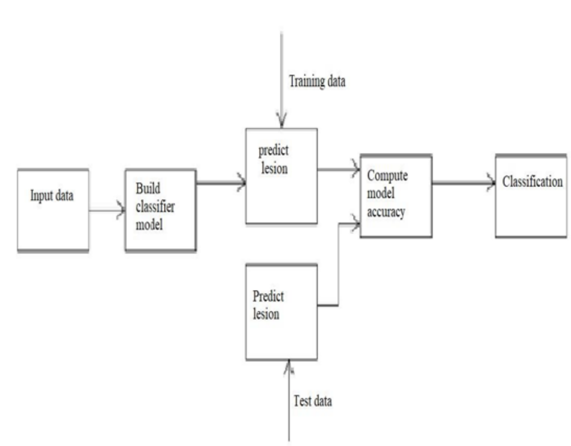

Fig.2 Architecture diagram

This description encompasses intricate details regarding the organization of components, their interplay, and the overall conduct of the system. The objective is to craft a comprehensive document that not only encapsulates the present state of the system but also facilitates forthcoming modifications and advancements.

The allocation of functionality onto both hardware and software components stands out as a pivotal facet of system architecture. This entails specifying the distribution of diverse tasks and operations across the underlying hardware infrastructure and corresponding software modules. The aim is to ensure the efficient and effective utilization of the system's computational resources.

Similarly crucial is the alignment of software architecture with the hardware architecture. This step requires harmonizing the software components with the available hardware resources, optimizing performance, and guaranteeing that the overall system fulfills its functional and non-functional requisites. It addresses concerns such as load balancing, resource utilization, and scalability.

Human interaction with system components forms an integral aspect of system architecture. This involves comprehending how users engage with the system, encompassing user interfaces, input mechanisms, and the overall user experience. Beyond technical functionalities, this aspect considers the usability and accessibility of the system, ensuring a positive interaction between users and the implemented architecture.

In essence, system architecture embodies a holistic approach to designing and delineating complex systems. It transcends a mere depiction of components and interactions by delving into the interconnections between software and hardware, along with the dynamics of human-system interaction. A well-defined system architecture provides a blueprint for development, maintenance, and evolution, thereby contributing to the triumph and sustainability of a technological solution.

V. RESULTS AND DISCUSSIONS

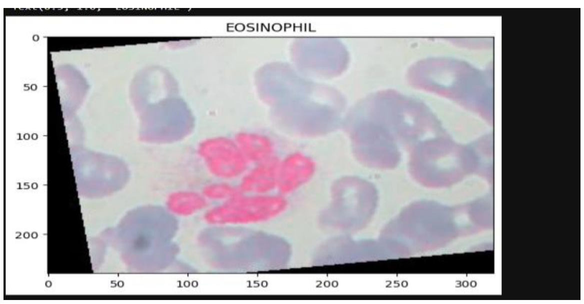

Fig.3 Eosinophil

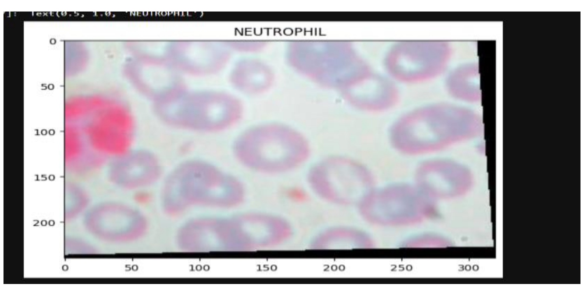

Fig.4 Neutrophil

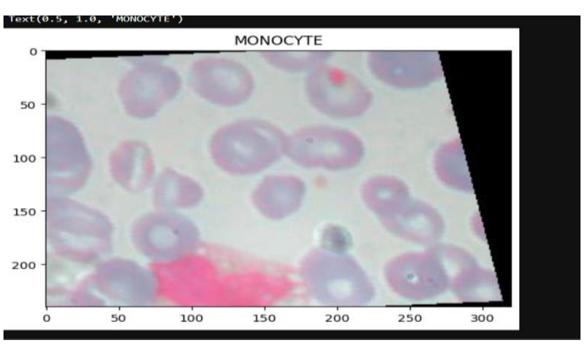

Fig.5 Monocyte

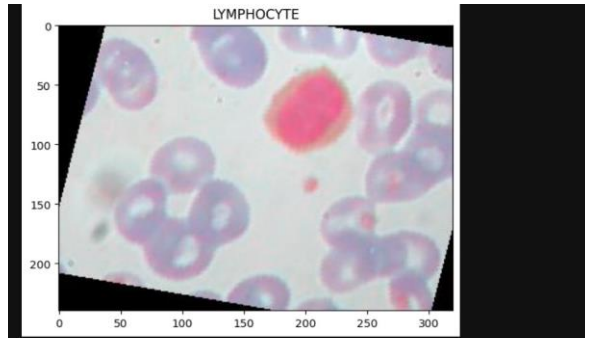

Fig.6 Lymphocyte

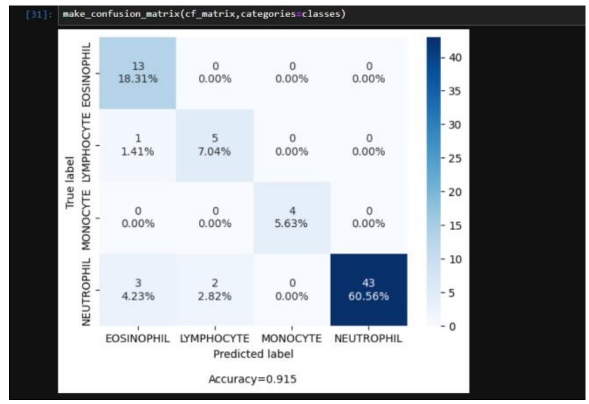

Fig.7 Accuracy

VI. CONCLUSION

White blood cells constitute a crucial component of human blood, distinguishing themselves through the possession of nuclei. This feature not only sets them apart from other blood cells but also allows for differentiation among various white blood cell types and subtypes. This project provides a comprehensive exploration of white blood cell types and their structures, shedding light on the diverse functions inherent in this vital component of the circulatory system. Understanding the nuanced characteristics of white blood cells is imperative for grasping their integral role in maintaining overall health and responding to potential threats.

Moving beyond theoretical discourse, the project introduces an innovative automatic white blood cell classification system. This system encompasses distinct stages, including image acquisition, pre-processing, segmentation, and feature extraction. The primary objective is to automate these processes, thereby improving the efficiency and accuracy of white blood cell classification. This technological advancement holds promise for significant strides in medical diagnostics and research.

The emphasis on automation addresses the limitations associated with manual methods in white blood cell analysis, such as labor-intensive procedures and subjective interpretations. By harnessing technology and image processing techniques, the project aims to streamline and standardize the classification of white blood cells, providing a more efficient and reliable approach.

In essence, this project not only delves into the fundamental aspects of white blood cells but also takes a pragmatic step towards advancing the field. The development of an automatic classification system aligns with the broader goal of leveraging technology to enhance our understanding of the immune system and improve medical diagnostics in the realm of hematology.

REFERENCES

[1] Khamael AL-Dulaimi, Jasmine Banks, Vinod Chandran, Inmaculada Tomeo-Reyes and Kien Nguyen, "Classification of White Blood Cell Types from Microscope Images: Techniques and Challenges," Link

[2] Carleton HM, Drury RAB, Wallington EA. Carleton's histological technique: Oxford University Press, USA; 1980.

[3] Clark VL, Kruse JA. Clinical methods: the history, physical, and laboratory examinations. Jama. 1990; 264(21):2808-9.

[4] Ciresan, D. C., Giusti, A., Gambardella, L. M., & Schmidhuber, J. (2013). "Mitosis detection in breast cancer histology images with deep neural networks." Medical Image Computing and Computer-Assisted Intervention, 16(1), 411-418.

[5] Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M., & Summers, R. M. (2016). "ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases." In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 3462-3471.

[6] Xu, J., Luo, X., Wang, G., Gilmore, H., & Madabhushi, A. (2016). "A Deep Convolutional Neural Network for segmenting and classifying epithelial and stromal regions in histopathological images." Neurocomputing, 191, 214-223.

[7] Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). "A survey on deep learning in medical image analysis." Medical Image Analysis, 42, 60-88.

[8] Sirinukunwattana, K., Raza, S. E. A., Tsang, Y. W., Snead, D. R., Cree, I. A., & Rajpoot, N. M. (2016). "Locality Sensitive Deep Learning for Detection and Classification of Nuclei in Routine Colon Cancer Histology Images." IEEE Transactions on Medical Imaging, 35(5), 1196-1206.

[9] Bentaieb, A., Hamarneh, G. (2015). "Boundary-driven patch-based segmentation using deep learning for whole slide histopathology images." In Medical Image Computing and Computer-Assisted Intervention (MICCAI), 2015.

[10] Cruz-Roa, A., Basavanhally, A., González F., et al. (2014). "Automatic detection of invasive ductal carcinoma in whole slide images with Convolutional Neural Networks." In SPIE Medical Imaging, International Society for Optics and Photonics.