WWW.IJRPR.COM

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Blood Cells Count Using Deep Learning

Sarika Buchake[1], Payal Shete[2], Tushar Shete [3], Dr. Anand Khatri[4]

[1,2,3] Undergraduate Student, Department of Computer Science and Engineering, JCOE, Kuran, Pune-4105, India

[4] Professor, Department of Computer Science and Engineering, JCOE, Kuran, Pune-410502, India

A B S T R A C T

The Complete Blood cells count has an important role in medical diagnosis to check common fitness conditions. Blood cells are traditionally counted using Hemocytometer with laboratory compounds and chemical compounds. It is so time consuming. In this paper, we propose a deep learning neural network based architecture to accurately detect and count various types of blood cells (RBCs, WBCs, Platelets,etc). The Convolutional Neural Network is used for classification and ResNet is used for feature extraction and improving the accuracy of blood cells counting. ResNet algorithm gives about 99% accuracy which is very good.

Keywords: Blood cells, ResNet, Deep learning, Convolutional Neural Networks, blood cell count, machine learning, image classification, image processing, blood cells detection.

Introduction

Blood is a unique kind of circulating connective tissue that carries oxygen from the lungs to every cell in the human body. Oxygen is necessary for metabolism in the body's cells, and the blood transports it from the lungs to the cells. In this way, blood supplies nutrients to cells, transports hormones, and removes undesirable substances that are eventually expelled by organs such as the liver, kidneys, or intestine. Furthermore, the carbon dioxide produced during metabolism is transported back to the lungs via the blood, where it is exhaled. Blood consists of cell fragments and plasma, which makes up the liquid component. Platelets are responsible for blood clotting, while red blood cells (RBCs) make up 40–50% of total blood volume and deliver oxygen and carbon dioxide. [1]

The cell fragments are mostly made up of white blood cells (WBCs), which account for 1% of the total blood volume and are responsible for immunity. Depending on the presence of granules, WBCs can be divided into two broad categories: granulocytes and a granulocytes (non-granulocytes). Neutrophils, eosinophils, and basophils are considered to be granulocytes, while lymphocytes and monocytes fall under a granulocytes. Immature granulocytes (IG) are released into the bloodstream from the bone marrow in their undeveloped form as WBCs. With the exception of blood from newborns or pregnant women, the presence of IG (promyelocytes, myelocytes, and metamyelocytes) in the blood indicates an early response to an infection, inflammation, or another type of issue with the bone marrow, such as leukemia. White blood cells, sometimes referred to as erythroblasts, are infection fighters that split themselves in order to identify, recognize, and attach to foreign proteins found in bacteria, viruses, and fungi in order to combat diseases and infections [2].

Red blood cells, or erythroblasts, aid tissues in producing energy by delivering the right amount of oxygen. Waste in the form of carbon dioxide is also created during the creation of energy. Erythroblasts, which are immature red blood cells, are commonly seen in the blood of newborns between the ages of 0 and 4 months. Red blood cells are in charge of delivering that carbon dioxide to the lungs so that it can be exhaled. After the neonatal period (0-4 months), their presence in human blood suggests significant issues, such as stress, injured bone marrow, or malignant tumors that can develop into cancer or benign tumors that expand but do not spread to other areas of the body. Thrombocytes, also known as platelets, are crucial to the immune system since their main job is to prevent bleeding. The brain transmits a warning signal to the platelets if there is bleeding from an injury or blood vessel damage somewhere in the body. The platelets migrate to the site of injury, clump together, and create a clot that seals the blood vessel and stops the bleeding. Additionally, they are essential for tissue regeneration and remodeling, which helps to stop the spread of tumors and the leakage of vesicant fluids. Less than 1% of blood volume is made up of them. The average proportion of neutrophils in the blood is between 0 and 6%, while eosinophils make up between 1 and 3%, basophils between 0 and 1%, lymphocytes between 25 and 33%, and monocytes between 3 and 10% of the leukocytes circulating in the blood [4].

Literature Review

Allaparthi HemaSri and Mopuru Devi Sreenidhi conducted a study titled "Detection of RBCs, WBCs, Platelets Count in Blood Sample by using Deep Learning," here they develop a deep learning model to automate the process of counting of red blood cells (RBCs), white blood cells (WBCs), and

platelets. They uses convolutional neural networks (CNNs) to analyze blood smear images, achieving accuracy in cell detection and classification. This gives the potential of CNNs in automating hematological analyses, reducing dependance on manual counting methods.[1]

In the study "Deep Learning Segmentation and Classification of Red Blood Cells Using a Large Multi-Scanner Dataset," Mohamed Elmanna et al. shows the challenges of variability in blood smear images gets from different scanners. They gives a deep learning framework for the segmentation and classification of RBCs, leveraging a diverse dataset to increase the model's Fault tolerance across various imaging conditions. Their result highlights the importance of large, heterogeneous datasets in training models capable of generalizing well to different clinical settings.[2]

Lee, Chen, and Lin, in their research "Complete Blood Cell Detection and Counting Based on Deep Neural Networks," proposed a detailed system for blood cell detection and counting using deep neural networks. Their model combines image preprocessing techniques with a deep learning architecture to accurately identify and quantify different blood cell types. The study reveals the efficiancy of deep neural networks in handling the complexities with blood cell morphology and distribution.[3]

Alam and Islam's 2019 study, "Machine Learning Approach of Automatic Identification and Counting of Blood Cells," analyzed the application of machine learning techniques in hematology. They developed a system that combined image processing methods with machine learning algorithms to automatically identify and count blood cells. Their approach demonstrated improvements in processing time and accuracy compared to traditional manual methods, emphasizing the benefits of automation in clinical diagnostics.[4]

Novia et al., in their 2023 paper "White Blood Cell Classification of Porcine Blood Smear Images," investigated the classification of WBCs in porcine blood samples using deep learning models. They applied a DenseNet-169 architecture to classify different WBC types, achieving high accuracy. This study contributed to the understanding of deep learning applications in veterinary hematology and provided insights applicable to human medical diagnostics.[5]

Lamia Alhazmi's 2022 research, "Detection of WBC, RBC, and Platelets in Blood Samples Using Deep Learning," presented a deep learning-based approach for the detection of various blood cell types. The study utilized a CNN model trained on blood smear images to identify and classify RBCs, WBCs, and platelets, achieving significant accuracy improvements over traditional methods. This work reinforced the potential of deep learning in enhancing the efficiency and reliability of hematological analyses.[6]

Collectively, these studies illustrate the advancements in applying deep learning techniques to blood cell detection and classification. The integration of CNNs and other deep learning architectures has led to significant improvements in accuracy, efficiency, and automation in hematological diagnostics. However, challenges such as variability in imaging conditions, the need for large and diverse datasets, and the interpretability of deep learning models remain areas for further research and development.[7]

Methodology

A. Data Collection:

Gather a diverse set of labeled microscopic images of blood cells from reliable sources to ensure comprehensive training data. Implement techniques such as rotation, flipping, and color adjustments to enhance the dataset and improve model generalization. Image Preprocessing: Use normalization, noise reduction, and contrast enhancement to improve the quality of input images, reducing errors in counting and classification.

B. Preprocessing:

Use normalization, noise reduction, and contrast enhancement to improve the quality of input images, reducing errors in counting and classification.

C. Data Partitioning:

The preprocessed data is divided into two subsets:

- Training Set: Used to train the deep learning models.
- Testing Set: Used to evaluate model performance on unseen data.

A typical split might be 80% training and 20% testing or 70/30 depending on dataset size.

D. Model Selection and Classification:

Multiple Learning models are used:

Deep Neural Network (DNN): Fully connected layers, used for basic image classification.

Convolutional Neural Network (CNN): Effective for image feature extraction and classification.

ResNet-50: A deep residual network with skip connections to prevent vanishing gradients.

MobileNet: A lightweight CNN optimized for mobile and embedded devices.

Prediction / Classification:

Based on model output, images are classify into three groups RBCs(Red Blood Cells), WBCs(White blood cells) and Platelets

E. Evaluation:

There are various evaluation matrices are used for evaluation are Accuracy, Precision, Recall, F1-Score, Confusion Matrix, Validation curves to assess training effectiveness.

Dataset Used

The BCCD (Blood Cells Count and Detection) dataset includes images of different types of blood cells, specifically Red Blood Cells (RBC), White Blood Cells (WBC), and Platelets. It is a small-scale dataset used for object detection and classification, with 364 images labelled across the three cell types.

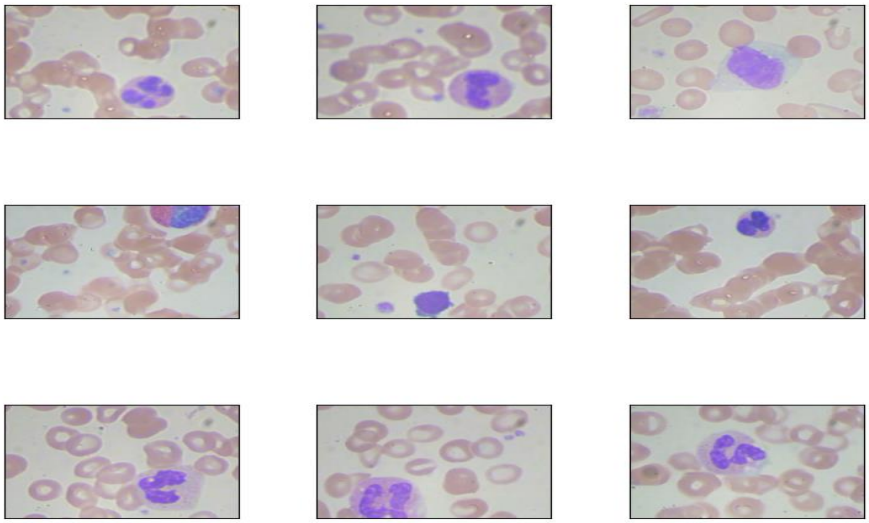

Fig 1: Dataset includes images

Architectural Design

Architecture design of the model is shown in fig.2 below in which the blood cells dataset is used for training and testing of the Resudial Network. The dataset is Splits into two Parts training set and testing set. Then using the training part the model is gets trained and using testing part the model gets evaluated using various matrices**.**

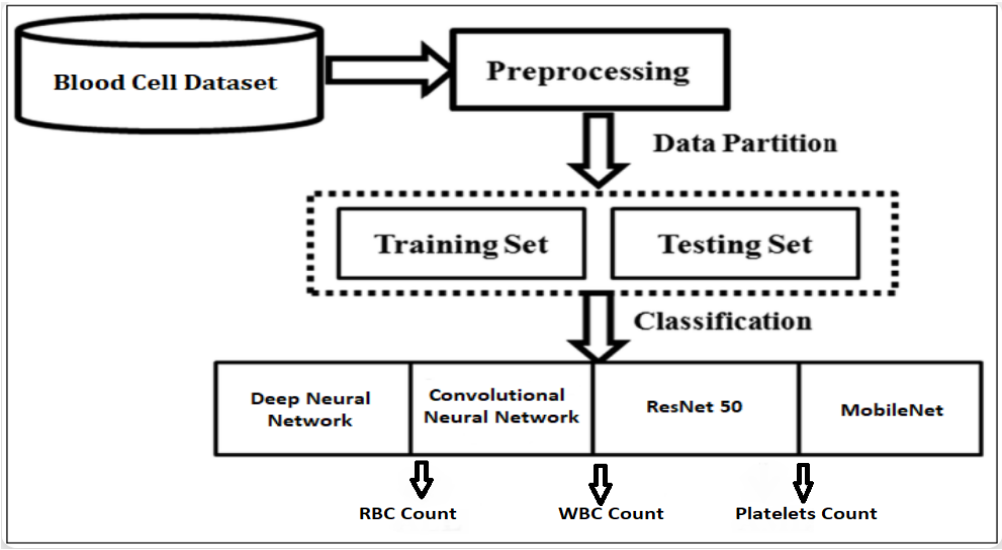

Fig 2: Architecture design**.**

System Architecture

Here we are taking a microscopic image of the blood sample which is treated with some chemicals. After acquisition of image we normalize it in preprocessing stage. This Preprocessed image is feeded to the ResNet Model which extracts the features from image are RBCs, WBCs, Platelets, etc. Based on feature extracted it predict the blood cells count.

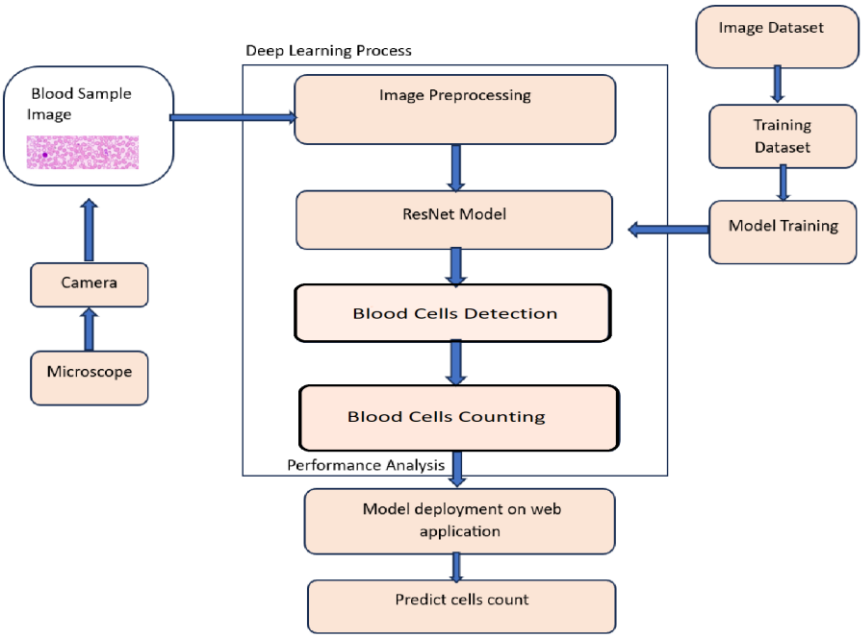

Fig 3: system architecture

Acknowledgements

We would like to say thank you sincerely to our guide Dr.A.A.Khatri sir and the Department of Computer Engineering, Jaihind College of Engineering, Pune, for their guidance and support throughout this project.

Results

The result of the used in ResNet model is given in the Fig 4. In which the model detects the RBCs, WBCs, Platelets in the blood sample image . Based on detection of image after applying some logic we count the total count of RBCs, WBCs and Platelets from image

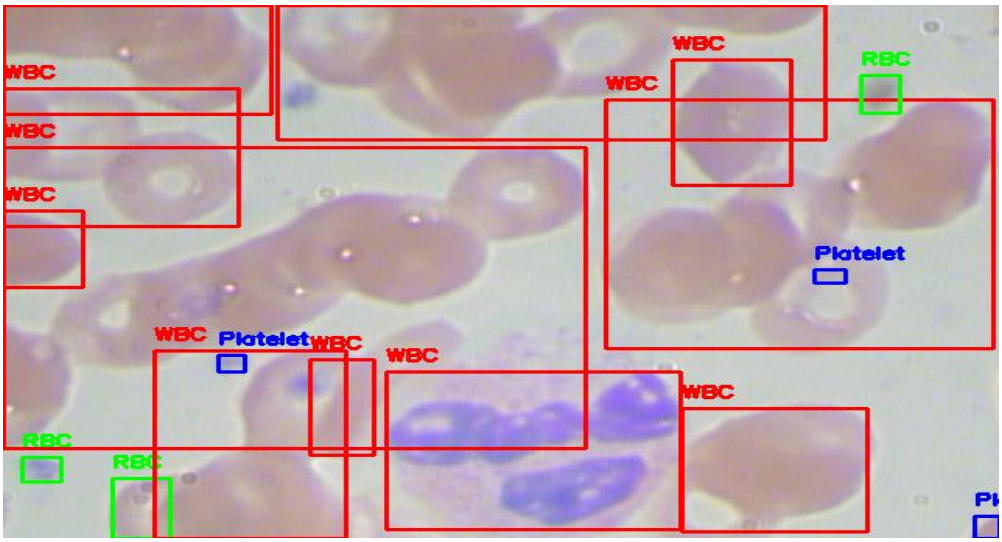

Fig 4. Detection of RBCs, WBCs, Platelets

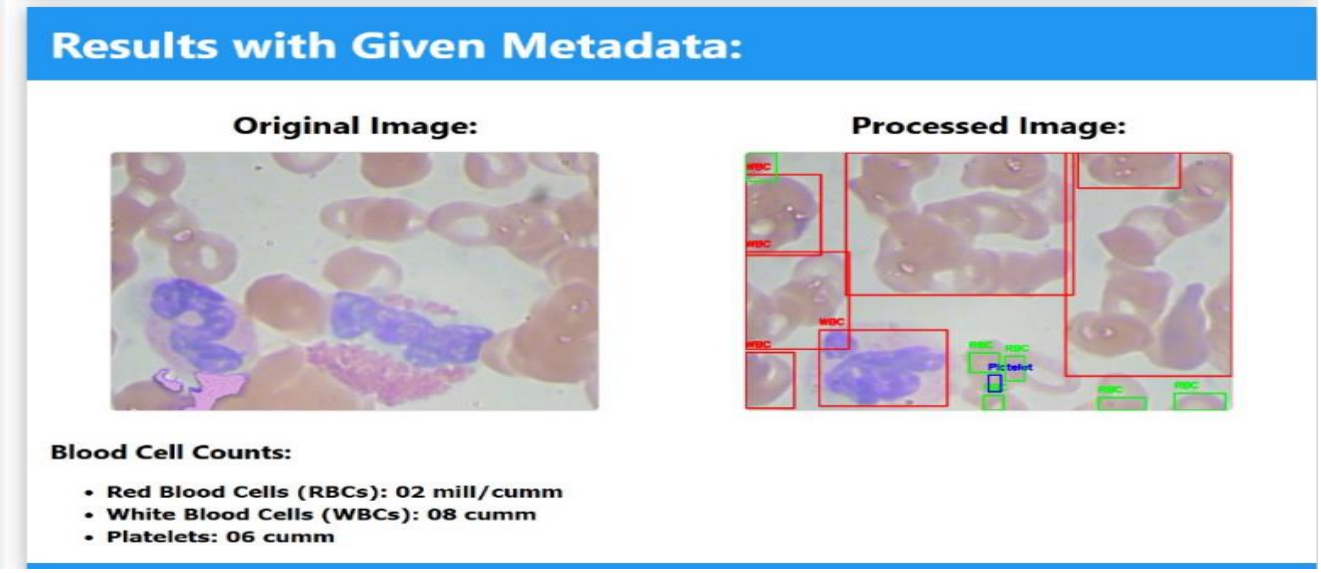

Fig 5. Cells count

Future Scope

The future scope of deep learning-based blood cell counting is vast, with potential advancements in accuracy, speed, and integration into healthcare systems. Future research can focus on enhancing model generalization across diverse datasets, improving robustness against variations in imaging conditions. The integration of multimodal learning, combining cell morphology with genomic data, could enhance disease diagnosis. Further, regulatory approval and clinical adoption will be crucial, requiring explainable AI models for transparent decision-making. Ultimately, these advancements can contribute to early disease detection, personalized treatments, and improved global healthcare outcomes.

Conclusion

This project began with the interest of using Deep Learning techniques to assist health professionals in their daily activities by automating tasks, allowing more important tasks to receive more attention. It was realized that it would be possible to assist professionals in analyzing blood samples by identifying and counting cells, generating subsidies for generating elements of a complete blood count (CBC), an essential examination in the identification of many diseases. To do this, it was necessary to understand the entire process of producing a CBC and also to find ways to associate the concepts of Deep Learning in this process.

Through training an intelligent computer model capable of recognizing the different blood cells in an image, the count of all types of cells was developed with satisfactory precision. The developed model shows potential to assist in the work of examination analysis professionals and also in cost reduction, since there is machinery involved the current process for producing CBCs. However, with the current results, it is not possible to produce a complete CBC, because, due to the limitations of the dataset used, it was not possible to carry out the individual classification of the white cells, only performing the general count of them.

References

Van der Geer, J., Hanraads, J. A. J., & Lupton, R. A. (2000). The art of writing a scientific article.*Journal of Science Communication, 163*, 51–59.

Strunk, W., Jr., & White, E. B. (1979).*The elements of style* (3rd ed.). New York: MacMillan.

Mettam, G. R., & Adams, L. B. (1999).How to prepare an electronic version of your article. In B. S. Jones & R. Z. Smith (Eds.), *Introduction to the electronic age* (pp. 281–304). New York: E-Publishing Inc.

Fachinger, J., den Exter, M., Grambow, B., Holgerson, S., Landesmann, C., Titov, M., et al. (2004).Behavior of spent HTR fuel elements in aquatic phases of repository host rock formations, 2nd International Topical Meeting on High Temperature Reactor Technology. Beijing, China, paper #B08.

Fachinger, J. (2006). Behavior of HTR fuel elements in aquatic phases of repository host rock formations.*Nuclear Engineering & Design,236*, 54.