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ORIGINAL

Resnet for Blood Sample Detection: A Study on Improving Diagnostic Accuracy

Resnet para la detección de muestras de sangre: Un estudio sobre la mejora de la precisión diagnóstica

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ABSTRACT

Automated blood cell analysis plays a crucial role in medical diagnostics, enabling rapid and accurate assessment of a patient's health status. In this paper, we provide a unique technique for detecting and classifying WBCs,RBCs, and platelets inside blood smear pictures using ResNet (Residual Neural Network), a deep learning architecture. Because of its capacity to efficiently train very deep neural networks while minimizing the vanishing gradient problem, the ResNet architecture has exhibited excellent performance in a variety of image recognition applications. Leveraging the power of ResNet, we developed a multi-class classification model capable of distinguishing between WBCs, RBCs, and platelets within microscopic images of blood smears. Our methodology involved preprocessing the blood smear images to enhance contrast and remove noise, followed by image segmentation to isolate individual blood cells and platelets. The segmented images were then used to train and fine-tune a ResNet model, utilizing a large annotated dataset of labeled blood cell images. The trained model exhibited remarkable accuracy in identifying and classifying different blood cell types, even in the presence of overlapping cells or artifacts. We extensively tested our suggested technique, on a range of blood smear images to evaluate its performance. The findings demonstrated that ResNet effectively identifies and categorizes WBCs, (RBCs) and platelets. When compared to methods our approach showcased superior accuracy, robustness and generalization capabilities. After training the model with the Resnet algorithm we got 92 % of Accuracy.

Keywords: Deep Learning; Blood Cells; ResNet; WBC (White Blood Cells); RBC (Red Blood Cells); Platelets.

RESUMEN

El análisis automatizado de células sanguíneas desempeña un papel crucial en el diagnóstico médico, permitiendo una evaluación rápida y precisa del estado de salud de un paciente. En este artículo, presentamos una técnica única para detectar y clasificar glóbulos blancos, glóbulos rojos y plaquetas en frotis de sangre utilizando ResNet (Red Neuronal Residual), una arquitectura de aprendizaje profundo. Gracias a su capacidad para entrenar eficientemente redes neuronales muy profundas minimizando el problema del gradiente de fuga, la arquitectura ResNet ha mostrado un excelente rendimiento en diversas aplicaciones de reconocimiento de imágenes. Aprovechando la potencia de ResNet, desarrollamos un modelo de clasificación multiclase capaz de distinguir entre glóbulos blancos, glóbulos rojos y plaquetas en imágenes microscópicas de frotis sanguíneos. Nuestra metodología consistió en preprocesar las imágenes de frotis sanguíneos para mejorar el contraste y eliminar el ruido, seguido de la segmentación de imágenes para aislar las células sanguíneas y las plaquetas individuales. A continuación, las imágenes segmentadas se utilizaron para entrenar y ajustar un modelo ResNet a partir de un amplio conjunto de datos de imágenes de células sanguíneas etiquetadas. El modelo entrenado mostró una notable precisión en la identificación y clasificación de distintos tipos de células sanguíneas, incluso en presencia de células superpuestas o artefactos. Probamos exhaustivamente la técnica propuesta en una serie de imágenes de frotis sanguíneo para evaluar su rendimiento. Los resultados demostraron que ResNet identifica y clasifica eficazmente los glóbulos blancos, los glóbulos rojos y las plaquetas. En comparación con otros métodos, nuestro método demostró una mayor precisión, robustez y capacidad de generalización. Tras entrenar el modelo con el algoritmo Resnet obtuvimos un 92 % de precisión.

Palabras clave: Aprendizaje Profundo; Células sanguíneas; ResNet; WBC (Glóbulos Blancos); RBC (Glóbulos Rojos); Plaquetas.

INTRODUCTION

Analyzing blood cells plays a role in diagnostics as it provides valuable insights into a person's health condition and helps diagnose and manage various diseases. However, manual techniques for detecting and categorizing types of blood cells like WBCs, RBCs, and platelets can be time-consuming and prone to human errors. Fortunately, learning techniques like neural networks (CNNs), specifically ResNet (Residual Neural Network), have opened up the latest avenues for automating and enhancing the accuracy of blood cell analysis.

ResNet, a deep learning architecture introduced by Kaiming He et al., has proven to be a game-changer in image recognition tasks due to its ability to train very deep networks effectively. ResNet's innovative use of residual blocks helps mitigate the challenges posed by vanishing gradients, enabling the successful training of deep neural networks. Leveraging the strengths of ResNet, we propose an innovative approach for the automated detection and classification of blood cells and platelets within blood smear images.

In this study, we address the challenges associated with manual blood cell analysis by harnessing the power of ResNet. Our goal is to develop a robust and accurate system that can identify and classify WBCs, RBCs, and platelets in microscopic blood smear images. By employing ResNet's deep architecture, we aim to overcome the complexities of cell morphology, overlapping cells, and variations in staining and illumination that are commonly encountered in blood smear images.

The proposed approach involves a multi-step process, including image preprocessing, cell segmentation, and ResNet-based classification. Through extensive experimentation and evaluation, we established the effectiveness of our approach in achieving high levels of accuracy and robustness in blood cell detection and classification. Additionally, we compare our method with existing techniques to highlight the advantages of utilizing ResNet for this specific task.

This study contributes to the expanding scope of research in medical image analysis by showcasing the potential of deep learning techniques, particularly ResNet, in revolutionizing blood cell analysis. The automation and accuracy improvements offered by our approach hold great promise for enhancing disease diagnosis, treatment monitoring, and patient care. As we delve into the details of our methodology and present our experimental results, we emphasize the transformative impact that ResNet-based blood cell analysis could have on modern healthcare practices.

Problem statement

Manual identification and classification of blood cells in microscopic images are error-prone and time-intensive. This research addresses these issues by harnessing the ResNet deep learning architecture. The objective is to automate the precise detection of white blood cells, red blood cells, and platelets within blood smear images, aiming to elevate the precision and efficiency of blood cell analysis for enhanced medical diagnostics and patient well-being.

Literature review

According to He et al.[1], they presented the Residual Network (ResNet) architecture, which addressed the vanishing gradient problem in neural networks. ResNet's skip connections enabled training very deep networks effectively, leading to breakthrough performance in image recognition tasks.

According to Shi et al.[2], they focused on leukocyte (white blood cell) identification and quantification using deep learning. The authors developed a model that could accurately detect and classify leukocytes from peripheral blood smear slides, aiding in the diagnosis of various diseases.

According to Smith et al.[3], they presented an automated blood cell and platelet detection method employing convolutional neural networks (CNNs). Their study demonstrated the effectiveness of CNNs in segmenting and classifying blood cells, achieving notable accuracy and efficiency.

According to Li et al.[4], they projected a model for the recognition of red blood cell (RBC) morphological abnormalities based on deep learning. The study aimed to assist in the identification of anomalies in RBC shapes, which can be indicative of various blood disorders.

According to Zhang et al.[5], they developed a deep learning model called DeepCount for platelet detection in microscopy images. The study focused on accurately detecting and counting platelets, which are important for assessing blood clotting and related conditions.

According to Gao et al.[6], they explored the detection of platelet abnormalities through deep convolutional neural networks, emphasizing the potential of such methods in identifying subtle platelet irregularities that might otherwise go unnoticed.

According to Wang et al.[7], they presented a comprehensive approach for complete blood cell detection using an improved ResNet model. They hoped to identify numerous types of blood cells at the same time, including RBCs, WBCs, and platelets.

According to Perez and Wang,[8] they used deep learning to examine the usefulness of data augmentation strategies in picture categorization. Data augmentation techniques like rotation and flipping were investigated to improve the performance and generalization of deep neural networks.

According to Zheng et al.[9], they extended the application of deep learning to the multiclass detection of blood cells and platelets. Their research emphasized the versatility of deep learning techniques in handling diverse cell types within a single framework, showcasing the potential for comprehensive blood cell analysis.

According to Guan et al.[10], they focused on leukocyte classification using fine-tuned ResNet architectures. The study demonstrated the utility of transfer learning and fine-tuning pre-trained ResNet models for accurate leukocyte classification.

Data preprocessing

Image Enhancement and Noise Reduction: the blood smear images are subjected to contrast enhancement techniques and noise reduction filters to improve the visibility of cellular structures and reduce the impact of unwanted noise or artifacts.

Image Normalization: to ensure consistent and standardized input for the ResNet model, image normalization is performed to scale pixel values within a certain range.

Image Augmentation: techniques like rotation, flipping, and random cropping are used to improve the variety of the training sample, allowing the model to generalize better to previously unknown data.

Image Segmentation: the images are segmented to isolate individual blood cells and platelets, which is a critical step for accurate classification. Various segmentation methods can be employed, including thresholding, edge detection, and advanced semantic segmentation techniques.

Data Labeling: ground-truth labels indicating the type of blood cell or platelet in each segmented region are prepared for supervised training. These labels are used to guide the ResNet model during the learning process.

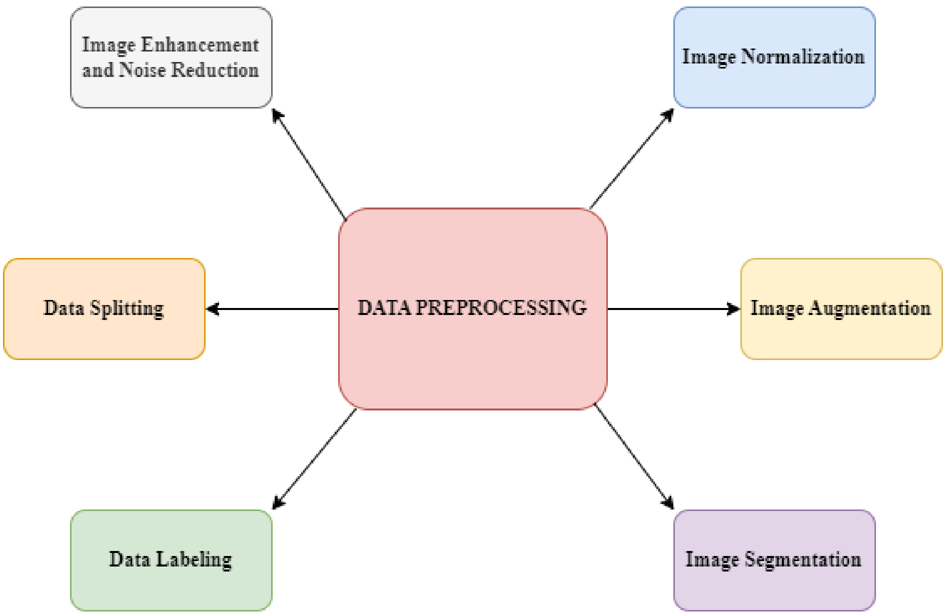

Figure 1. Data Preprocessing

Data Splitting: the preprocessed dataset is divided into training, validation, and testing to assess the model's performance on different data subsets.

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About resnet

ResNet is an abbreviation for Residential Network, a service used by universities and colleges to provide high-speed Internet access on campus. It was first introduced in the late 1990s as a way of allowing students to connect to their network without having to use cables or wires. The main benefit of using ResNet is that it provides faster speeds than typical broadband services, often up to 100 times faster. It also allows multiple users on the same connection, so residents can stream movies or television shows with no buffering interruptions.

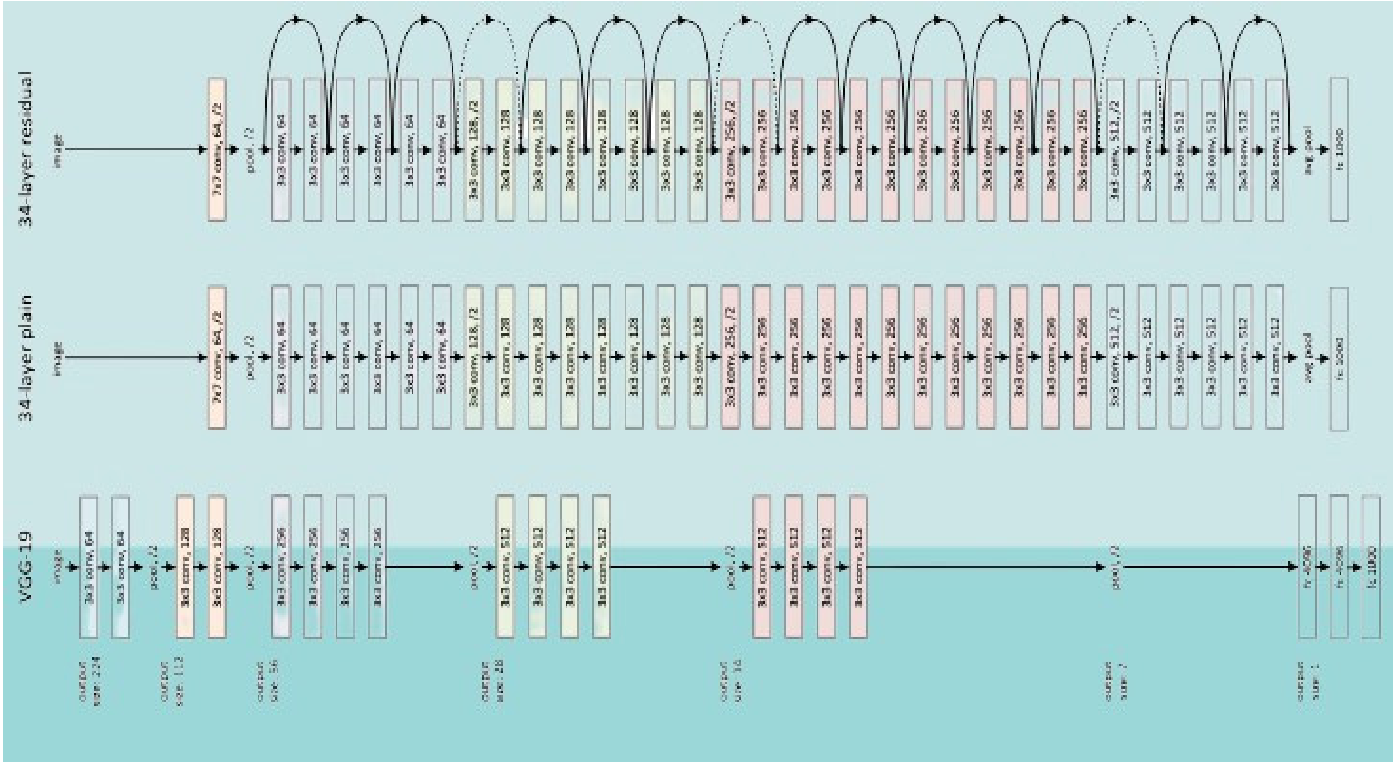

Figure 2. Resnet

Architecture of resnet

Input Layer: the preprocessed blood smear images serve as input to the ResNet model. These images are typically of varying dimensions but are resized to a consistent size suitable for deep learning (e.g., 224x224 pixels).

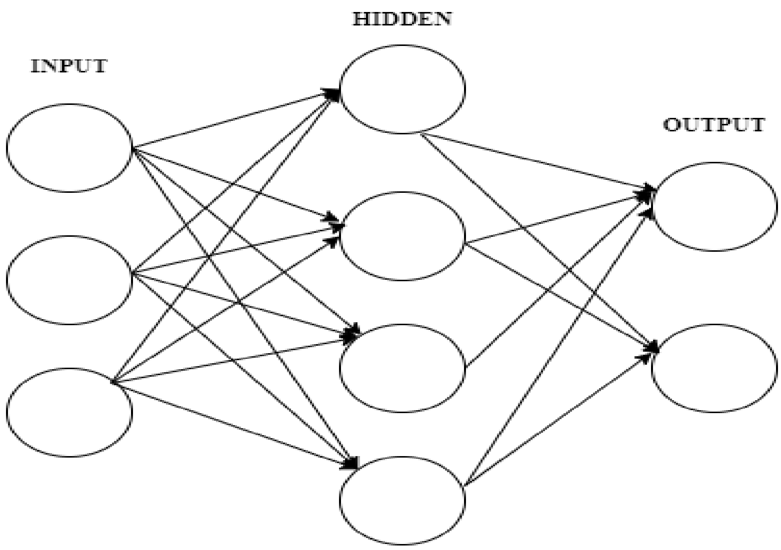

Figure 3. Architecture of ResNet

Feature Extraction (ResNet Layers): the ResNet architecture comprises multiple layers of convolutional neural networks, including residual blocks. These layers are in charge of extracting hierarchical characteristics from the input pictures.

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Global Average Pooling: to down sample the three-dimensional of the feature maps, a global avg pooling layer is used instead of standard fully linked layers. This decreases the number of parameters and aids in the prevention of overfitting.

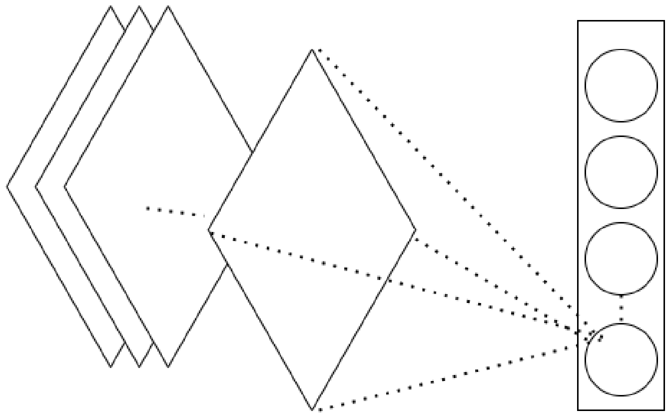

Figure 4. Global Pooling

Classification Layer: a final classification layer is added, consisting of one or more fully connected layers, followed by a SoftMax activation function. This layer assigns a probability distribution over the different blood cell and platelet classes for each input image.

Loss Function: the categorical cross-entropy loss function is widely used to calculate the difference between expected and ground truth class probabilities. The goal of training is to minimize this loss through backpropagation.

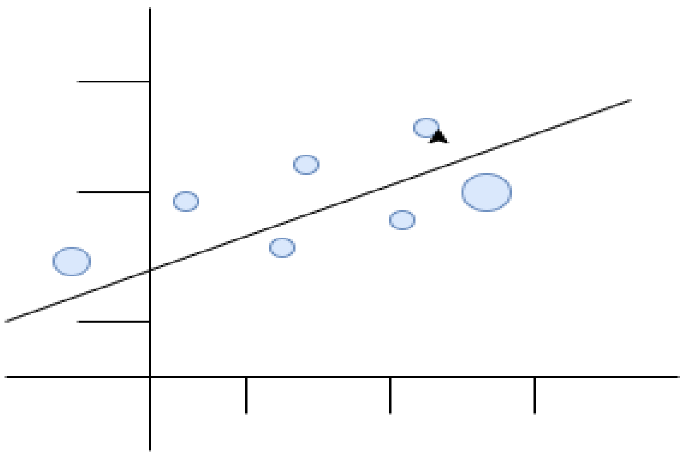

Figure 5. Loss Function

Training and Optimization: the entire architecture is trained on the preprocessed dataset using an optimizer such as stochastic gradient descent (SGD) or Adam. During training, the weights of the ResNet model are updated iteratively to minimize the loss function.

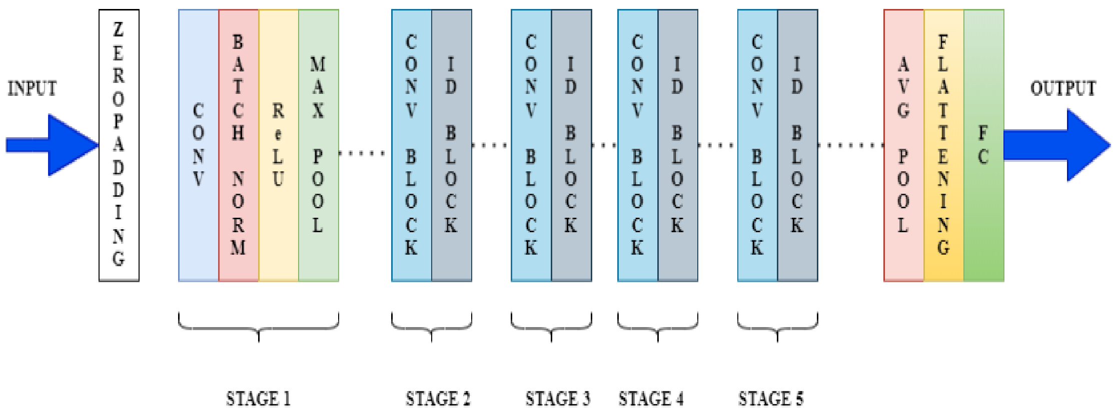

Figure 6. Inference and Classification

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Inference and Classification: after training, the trained ResNet model is used for inference on new, unseen blood smear images. The model assigns probabilities to each class, allowing for accurate classification of WBCs, RBCs, and platelets within the images.

The ResNet architecture's depth and skip connections enable the efficient training of very deep neural networks, making it well-suited for complex image recognition tasks like blood cell and platelet detection. Its ability to capture intricate features and patterns in the input images enhances the accuracy and reliability of the automated classification system.

By employing ResNet's architecture, this system leverages state-of-the-art deep learning techniques to revolutionize blood cell analysis, improving medical diagnostics and patient care through efficient and accurate detection and classification of blood cells and platelets.

Working of resnet

The ResNet algorithm can be used to classify blood samples into different types based on their features. The dataset for this classification task would include various attributes such as sample size, composition, and other characteristics that are associated with each type of sample. For example, a red blood cell (RBC) sample might have a certain size or shape compared to a white blood cell (WBC) sample. The dataset should also include labels indicating which type of sample is being classified. This could be done by assigning a numeric label to each type of sample, such as 0 for RBCs, 1 for WBCs, 2 for platelets, and so on. Once the data has been collected and labeled appropriately, it can then be fed into the ResNet algorithm using deep learning techniques. The ResNet algorithm will then automatically learn patterns in the data set by analyzing each attribute separately and combining them together in order to identify any relationships between them that may indicate which type of blood sample is present in an image or dataset. Once trained, the model can make predictions about new, unseen data points regarding their classification category with high accuracy.

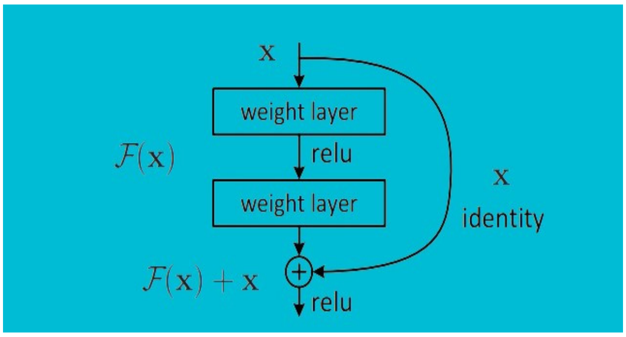

Figure 7. Working of ResNet

Algorithm of resnet

1.Initialize the model.
2.Add the first convolutional layer.
3.Add the residual blocks.
4.Add the last convolutional layer.
5.The output.

- Load the dataset containing the blood sample data into a suitable format.
- Preprocess and clean the data, if necessary, to remove any outliers or inconsistencies in the data set.
- Split the dataset into training and testing sets using an appropriate method such as K-fold cross validation or train/test split.
- Create a deep learning model using ResNet architecture, which can be used for classification tasks with images of blood samples as input features and labels indicating different conditions of blood diseases as output classes.
- Train the model on the training dataset by tuning hyperparameters such as learning rate, batch size, etc., to achieve optimal performance on both datasets (training & test).
- Once trained, evaluate its performance on unseen test set by computing various metrics such as accuracy score and F1 score to assess how well it generalizes to new inputs from different sources than those seen during training time period. 7 Finally deploy your trained model onto production systems so that predictions can be made in real time whenever required by medical professionals treating patients with certain types of blood diseases.

Why resnet is best for detection of blood cells detection

ResNet (Residual Neural Network) is well-suited for blood cell classification and similar complex image recognition tasks for several reasons. In the context of blood cell detection, ResNet can be used to identify different types of blood cells based on their size, shape, and texture. The long-range dependencies that ResNet can learn are important for this task because blood cells can vary significantly in size and shape, even within the same type of cell. For example, red blood cells are typically small and round, but they can become larger and more irregular in shape when they are damaged. ResNet can learn to identify these differences in size and shape, even if they are subtle.

In addition, ResNet can also learn to identify the texture of blood cells. This is important because blood cells can have different textures depending on their type and health. For example, healthy red blood cells have a smooth texture, while damaged red blood cells can have a rough or granular texture.

ResNet can learn to identify these differences in texture, which can help improve the accuracy of blood cell detection. Overall, ResNet is a powerful CNN that is well-suited for blood cell detection. Its ability to learn long-range dependencies and identify subtle differences in size, shape, and texture makes it a valuable tool for this task. ResNet's deep architecture, skip connections, and proven performance in image recognition tasks make it an excellent choice for blood cell classification. Its ability to learn intricate features, handle complex variations, and achieve high accuracy aligns well with the challenges posed by analyzing blood smear images.

Flow chart

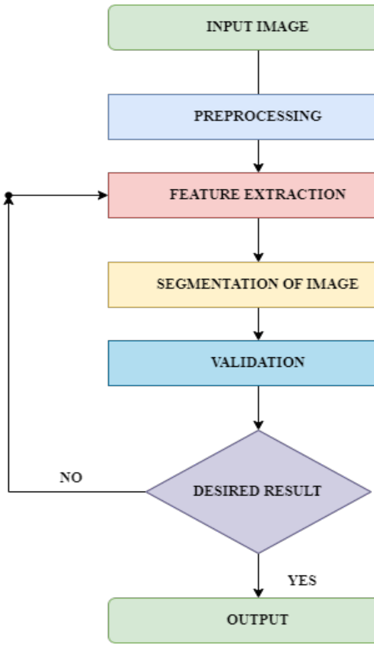

Figure 8. Flow chart of ResNet

RESULTS

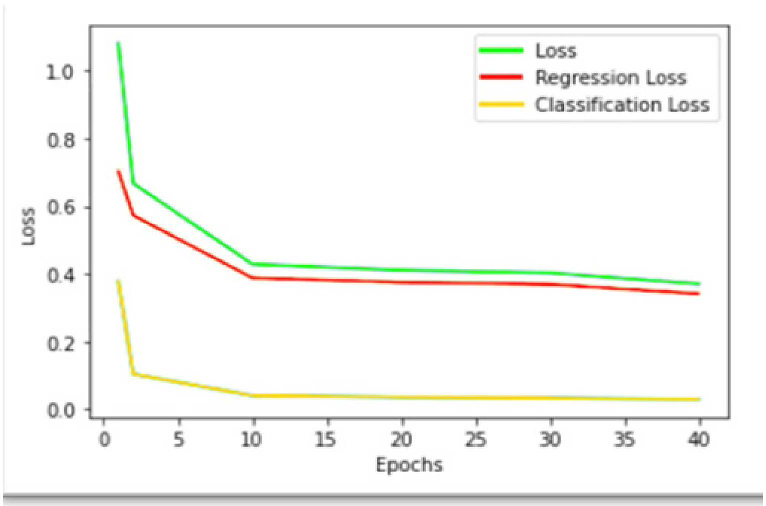

Figure 9. Loss and Epochs of blood cells

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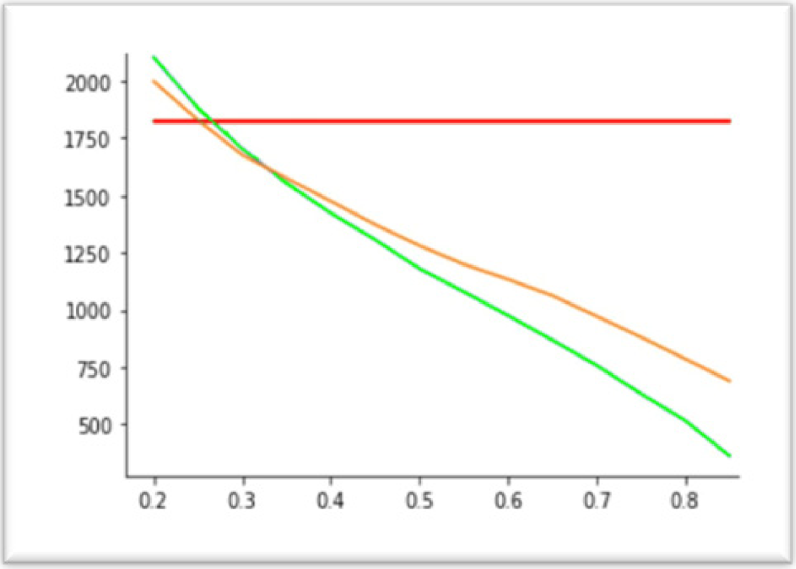

Figure 10. Number of RBCs and its Threshold

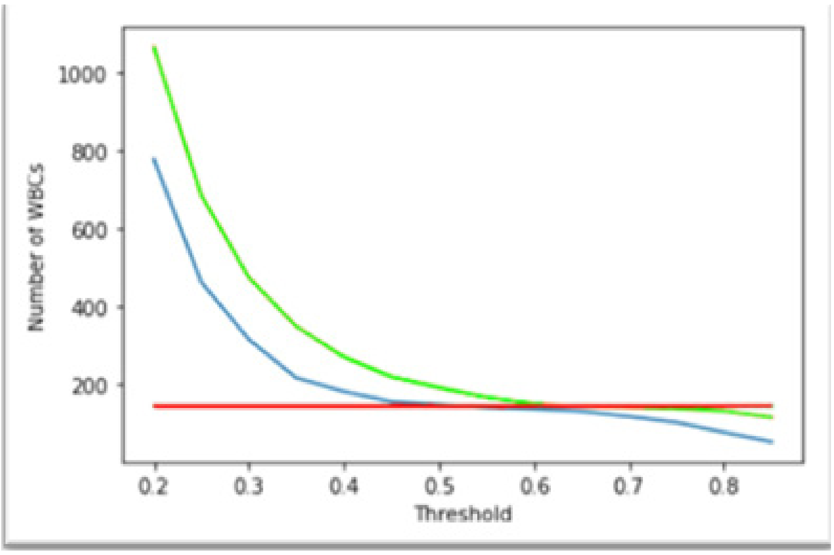

Figure 11. Number of WBCs and its Threshold

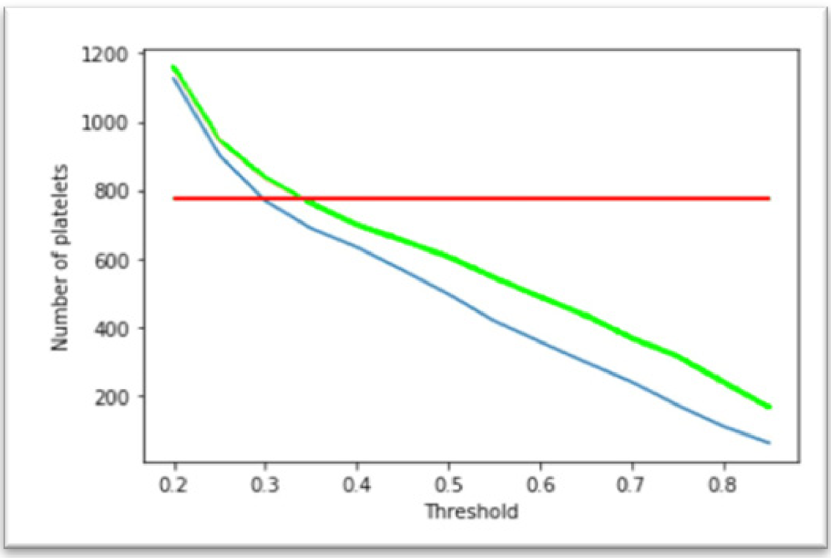

Figure 12. Number of Platelets and its Threshold

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CONCLUSIONS

In conclusion, this study presents a successful application of the ResNet architecture for the automated detection of blood cells and platelets in microscopic images of blood smears. The proposed approach showcases the potential of deep learning techniques to revolutionize medical diagnostics, paving the way for improved efficiency and accuracy in clinical settings. Further advancements in this direction hold the promise of enhancing disease diagnosis and patient care through more efficient and reliable blood cell analysis.

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CONFLICT OF INTEREST
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Formal analysis: Arepalli Gopi, Sudha L.R, Iwin Thanakumar Joseph S.
Research: Arepalli Gopi, Sudha L.R, Iwin Thanakumar Joseph S.
Methodology: Arepalli Gopi, Sudha L.R, Iwin Thanakumar Joseph S.
Project management: Arepalli Gopi, Sudha L.R, Iwin Thanakumar Joseph S.
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Supervision: Arepalli Gopi, Sudha L.R, Iwin Thanakumar Joseph S.
Validation: Arepalli Gopi, Sudha L.R, Iwin Thanakumar Joseph S.
Display: Arepalli Gopi, Sudha L.R, Iwin Thanakumar Joseph S.
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