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Classification of Blood Cells from Microscopic Images Using Shallow CNN

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***Abstract*— In recent years, various diseases such as anaemia, malaria, leukaemia, and other infections have significantly affected human health. Identifying these conditions requires blood testing, which serves as an initial step in detecting abnormalities in the human body. Traditionally, blood cell identification is performed manually, making the process time-consuming and prone to human error. To overcome these limitations, modern technological approaches offer automated solutions that improve accuracy and efficiency. These advancements help reduce processing time and minimize errors, making blood cell identification more reliable for diagnostic applications.**

In this work, we propose a solution for blood cell identification using deep learning techniques to classify different types of blood cells through Convolutional Neural Networks (CNN). This system is capable of identifying and classifying various blood cells such as Red Blood Cells (RBC), White Blood Cells (WBC), and platelets with the help of microscopic images. The model includes several preprocessing techniques, such as normalization, data augmentation, and noise removal, to enhance the quality of the input data.

In this system, we use a CNN model that can automatically extract features from the input data, such as shape, colour, and texture. This helps reduce the manual effort required for feature extraction. The CNN model is trained on a labelled dataset and evaluated using performance metrics such as accuracy, precision, recall, and F1-score. This approach helps automate the process of blood cell identification, reducing errors and minimizing the time required.

***Index Terms*— Deep Learning; Convolutional Neural Networks (CNN); Blood Cell Classification; Medical Imaging; Artificial Intelligence.**

I. INTRODUCTION

Blood plays a vital role in the human body by carrying oxygen and maintaining physiological balance. It is responsible for transporting oxygen, nutrients, hormones, and metabolic waste between organs.

Types of Blood Cells

- Red Blood Cells (RBC): Responsible for carrying oxygen throughout the body.
- White Blood Cells (WBC): Help defend the body against infections and foreign invaders.
- Platelets: Play a crucial role in blood clotting and wound healing.

The classification and counting of blood cells are essential for identifying various types of diseases in the human body.

- RBC: Anaemia
- WBC: Infections, Leukaemia
- Platelets: Bleeding disorders

Blood cell analysis is an important process in medical diagnostics. In traditional methods, blood cell classification is performed manually using a microscope. This process requires skilled laboratory technicians and is time-consuming. Additionally, there is a high chance of human error, as results may vary depending on the observer's experience and fatigue. With the increasing number of patients, these manual methods become inefficient and difficult to manage. To address these challenges, advancements in artificial intelligence and deep learning provide an effective solution. A Shallow Convolutional Neural Network (CNN) is a type of deep learning model that uses fewer layers and is well-suited for image classification tasks. It can automatically learn important features from images, such as shape, colour, and texture, while maintaining a simpler architecture compared to deep CNN models. In this work, a shallow CNN model is used to classify blood cells from microscopic images, helping to reduce complexity, improve efficiency, minimize manual effort, and save time.

The main objective of this project is to classify different types of blood cells, such as Red Blood Cells (RBC), White Blood Cells (WBC), and platelets, from microscopic images. For this purpose, a shallow CNN model is used, which consists of a smaller number of layers to perform classification efficiently. Another objective is to reduce computational complexity and processing time compared to deeper CNN models. This system is designed to improve accuracy by learning and extracting important features from images, such as shape, colour, and texture. It also helps reduce manual effort, which can lead to human errors and increased processing time.

The scope of this project is to develop an automated system for classification of blood cells from microscopic images using shallow CNN model. This system mainly focuses on identifying different types of blood cells such as RBC, WBC and Platelets. So, It help in medical laboratories to reduce manual work and improve the speed of the analysis that has done. The shallow CNN model is designed to work with less computational resources so it can be used in basic systems also. This project can be further extended to detect specific diseases based on blood cell abnormalities.

The main scope of this project is to develop an automated system for the classification of blood cells from microscopic images using a shallow CNN model. This system primarily focuses on identifying different types of blood cells, such as Red Blood Cells (RBC), White Blood Cells (WBC), and platelets. It helps medical laboratories reduce manual work and improve the speed of analysis. The shallow CNN model is designed to work with fewer computational resources, making it suitable for use on basic systems. Furthermore, this project can be extended to detect specific diseases based on abnormalities in blood cells.

II. LITERATURE REVIEW

In recent years many researchers have worked on classification of blood cells using deep learning techniques. So, most of the existing works are based on Convolutional Neural Networks (CNN) because they are very better for image classification tasks by extracting features from the images. These CNN models are trained on microscopic images to identify different types of blood cells such as Red Blood Cells (RBC), White Blood Cells (WBC) and Platelets. Some of the research is on deep CNN models with having large number of layers to achieve high accuracy but the complexity increases. These models can learn complex features from the images so they require high computational power and more training time because of this it becomes difficult to use them in real-time applications. To overcome this problem, we use shallow CNN models. Shallow CNN uses a smaller number of layers compared to deep CNN which helps to reduces the complexity. Even though it is simple it can still give good performance for classification when proper preprocessing techniques like normalization, noise removal and data augmentation are used. Previous studies also show that feature extraction like shape, colour and texture plays an important role in classification of blood cells. However, there is still a need to develop a model which is both efficient and accurate. So, in this work we are focusing on using shallow CNN model for classification of blood cells from microscopic images which helps to reduce computational cost and improve efficiency while maintaining good accuracy.

III. SYSTEM ANALYSIS

Existing Systems

Review of Existing systems for blood cell classification use traditional manual methods and deep learning techniques. In traditional method, the classification is done by lab technicians using microscope which takes more time and requires skilled professionals. There is also chance of human errors and the results may vary from person to person. In recent years, many systems are developed using deep learning models like Convolutional Neural Networks (CNN). These systems can automatically classify blood cells from microscopic images with high accuracy. Deep CNN models use large number of layers to extract complex features from the images. But these models require high computational power, more memory and longer training time. Some systems also use advanced techniques like transfer learning and hybrid models to improve performance. Even though they give good results, they are complex and difficult to implement in low resource environments. So, the existing systems either depend on manual work or use complex deep learning models. Because of this there is a need for a simple and efficient system. In this project we are using shallow CNN model which reduces complexity and gives good performance with less computational cost.

A. Requirement Gathering

Requirement gathering is the first and most important step in this project because before developing the system we need to understand what are the requirements and what type of problem we are going to solve. In this stage we collect all the necessary information related to blood cell classification and how the system should work. In this project the main requirement is to classify different types of blood cells from microscopic images because identifying blood cells manually is a difficult and time-consuming process and also there may be chances of human errors. So, we need to gather the requirements in such a way that the system can automatically detect and classify the blood cells accurately.

B. Functional Requirements

Fig. 1. System Flowchart of the Proposed Blood Cell Classification Model

1. The system should take microscopic blood cell images as input.
2. The system should preprocess the images using techniques like normalization, resizing and noise removal.
3. The system should apply shallow CNN model to extract features from the images.
4. The system should classify the blood cells into different types such as RBC, WBC and Platelets
5. The system should display the output result clearly.

C. Security

The Security is also an important requirement in this system because the system deal with medical data which is sensitive and should be protected. So, the system make sure that the data is safe and not accessed by unauthorized users. The system should provide basic security features like user authentication so that only authorized persons can access the system and perform operations. This helps to prevent misuse of the system.

IV. SYSTEM ARCHITECTURE

The diagram illustrates a complete pipeline for developing a machine learning model to analyze microscopic cell images. It begins with data collection, where microscopic images and their corresponding XML annotations are gathered. This is followed by preprocessing, which involves parsing the XML files, cropping individual cells (such as RBCs, WBCs, and platelets), and splitting the dataset into training, validation, and testing sets. In the feature extraction stage, images are standardized through normalization and enhanced using augmentation techniques, while resizing ensures uniform input dimensions suitable for model training.

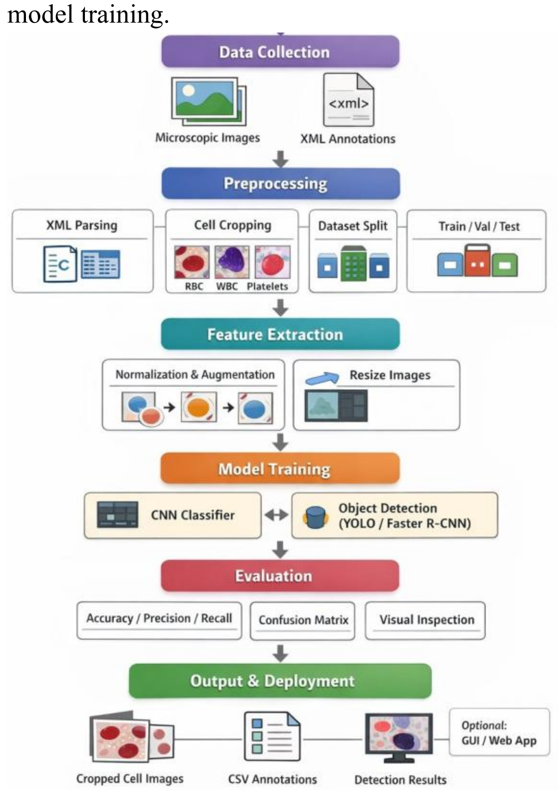

Fig. 2. Overall System Architecture

Next, the processed data is used in the model training phase, where models like CNN classifiers or object detection algorithms (e.g., YOLO or Faster R-CNN) learn to identify and classify cells. The model's performance is then assessed during the evaluation stage using metrics such as accuracy, precision, recall, and confusion matrices, along with visual inspection. Finally, in the output and deployment stage, the system produces cropped cell images, CSV-based annotations, and detection results, which can be integrated into applications like a GUI or web-based interface for practical use.

V. METHODOLOGY

Shallow Cnn Algorithm

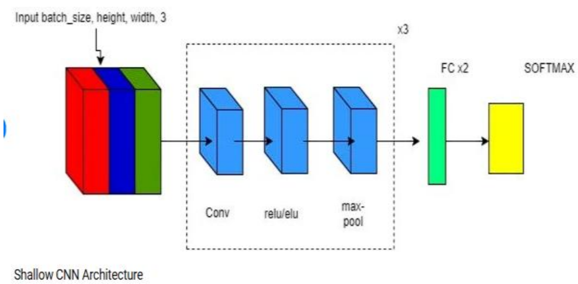

Fig. 3. Shallow CNN Architecture

In modern days to perform the blood cell identification we are using Deep Learning techniques like Convolutional Neural Networks (CNN). To make the process fast and simple we can use a Shallow CNN Architecture which is very helpful to identify the cells with less complexity. In traditional deep learning models, there are so many layers so it takes more time to train and needs more computer power. So to solve this problem the Shallow CNN uses only a few layers to get the work done quickly and accurately.

Layers in Shallow CNN Architecture

- Input Layer: This is the starting stage where we give the microscopic images of blood cells to the model. So, it takes the image size and the color channels like Red, Green, and Blue (RGB) to start the process.
- Convolutional Layer (Conv): This layer helps to extract features from the image like edges, shapes and textures. So, it reduces the manual effort of finding the features in the blood cells.
- Activation Layer (ReLU/ELU): After extracting the features we use this layer to help the model learn complex patterns. So, it helps the model to decide which information is important and which is not.
- Pooling Layer (Max-Pool): This layer helps to reduce the size of the image data while keeping the most important information. So, it reduces the time consuming and makes the model work faster without losing quality.
- Fully Connected Layer (FC): In this stage all the neurons are connected together to understand the features we extracted before. So, it prepares the data to make the final decision about the blood cell type.
- SoftMax Layer: This is the final stage which is used for classification. So, it gives the result by identifying whether the blood cell is a Red Blood Cell, White Blood Cell or Platelet.

1. Convolution Layer: Actually, this layer is used to extract features from the input image. So, the formula for convolution is: $S(I, j) = (I * K)(I, j) = \sum_m \sum_n I\,(i - m, j - n) \cdot K(m, n)$
Where I is the input image, K is the kernel/filter and S is the output feature map.

2. Activation Layer (ReLU / ELU):
After convolution we use an activation function. So, it helps the model to learn important patterns.

- ReLU is:

$$f(x) = \max(0, x)$$

- ELU is:

$$f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha(e^x - 1) & \text{if } x \le 0 \end{cases}$$

3. Pooling Layer (Max Pool): So, this layer reduces the size of the feature map but keeps the important information. The formula is:

$$P(i, j) = \max\{S(m, n) \mid (m, n) \in \text{pool window}\}$$

4. Fully Connected Layer: Actually, all the features are combined to make the final decision. So, the formula is:

$$y = f\left(\sum_i w_i\, x_i + b\right)$$

Where x_i are the inputs, w_i are the weights, b is the bias and f is the activation function.

5. SoftMax Layer (Classification): Finally, this layer is used for classification. So, it gives the probability of each class

6. $\sigma(z)_j = \frac{e^{z_j}}{\sum_k e^{z_k}}$

Where z_j is the input for class j and $\sigma(z)_j$ is the probability of class j.

Normal Vs Abnormal Blood Cells

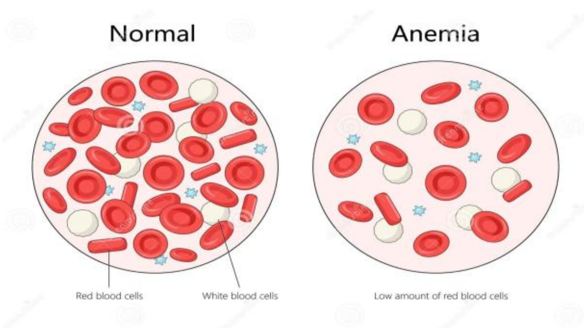

Fig. 5. Normal vs Abnormal Blood Cells

In traditional ways the doctors look at blood samples under a microscope to count the cells manually but this is a very slow process and there is a chance of human error. So, to solve this problem we use a Shallow CNN to automatically classify the blood cells from microscopic images like the one you provided.

Shallow CNN Classification of Blood Cells for Anaemia Detection

- Data Collection Stage: The system takes images of Normal blood and blood with Anemia. So normal images have many RBCs and anemia images have fewer RBCs.
- Feature Extraction: The Shallow CNN looks at features of the images. So, it sees high density of red circles in normal blood and more empty space in anemia blood.
- Comparison & Classification: The model learns the difference between patterns. So, it can classify blood as Normal or Anemia.
- Normal Classification: If the CNN sees many healthy RBCs, it classifies as Normal. So, it helps doctors know the blood is fine.
- Anemia Classification: If the CNN detects very few RBCs it identifies Anemia. So, it warns about the disease automatically.
- Noise Removal: Sometimes images have dust or marks like cells. So, the preprocessing removes noise and avoids counting mistakes.
- Final Output: After analysis the model shows the result on screen. So, doctors can see the condition quickly without manual counting.

VI. DISEASE DETECTION / ABNORMALITY CLASSIFICATION

A. Anemia Detection

For Anemia, the system looks at the Red Blood Cells (RBC). Normal blood has many RBCs that are round and healthy. In Anemia, there are fewer RBCs and some cells may look smaller or pale. The shallow CNN examines these features and classifies the sample as Normal or Anemia.

B. Leukemia Detection

Leukemia affects White Blood Cells (WBC). In normal blood, WBCs are fewer and evenly distributed. In Leukemia, WBC count increases and the cells may have irregular shapes. The shallow CNN learns these patterns and can identify whether the blood sample shows signs of Leukemia.

C. Platelet Abnormalities

Platelets are important for blood clotting. Normal blood has a certain number of platelets. Low or irregular platelets may indicate bleeding disorders. The shallow CNN detects these abnormalities and classifies the platelet condition as normal or abnormal.

VII. RESULTS AND DISCUSSION

After classification has done the system marks each type of blood cell using bounding boxes. Red boxes for WBC, green boxes for RBC, and blue boxes for Platelets. Abnormal cells are highlighted clearly so that doctors can see which cells are affected. This helps in fast and accurate diagnosis.

VII. CONCLUSION

In this project, we have developed a system to classify blood cells from microscopic images using a Shallow CNN model. This system can automatically identify Red Blood Cells, White Blood Cells, and Platelets with good accuracy. By using preprocessing techniques like resizing, normalization, noise removal, and data augmentation, the quality of input images is improved and the model performs better. Compared to traditional manual methods, this system reduces time, effort, and human errors in blood cell analysis. It also provides a faster way to detect abnormalities in blood samples, which helps doctors in diagnosing diseases like Anaemia, Leukaemia, and infections. Overall, this system shows that Shallow CNN can be a simple, effective, and practical solution for automated blood cell classification in medical laboratories and healthcare applications.

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