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Detection of Blood Cancer Cells using Microscopic Image

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Abstract

For the automatic diagnosis and classification of leukemia and leukemoid reactions, the IDB2 (acute lymphoblastic leukemia-image database) dataset has been utilized. This paper focuses on an automated method to differentiate between leukemoid and leukemia reactions using images of blood smear. MobileNetV3 is employed to classify and count WBC types from segmented images. The BCCD (Blood Cell Count Detection) dataset, which contains 364 images of blood smear and 349 single WBC type images, has been used in this work. The image segmentation algorithm incorporates Fuzzy C-means clustering, the snake algorithm, and fusion rules. For classification, the VGG19 CNN (Convolutional Neural Network) architecture-based deep learning technique is implemented. Python and Google colab is used for designing and executing the algorithm respectively.

Keywords: Python, Google Colab, MobileNetV3, VGG 19, Fuzzy C-Means

1. Introduction

Segmentation and cytoplasm of WBCs are extracted from microscopic images of blood. This process is important for analyzing the characteristics and morphology of the cells, which can provide valuable information about the immune system and the presence of diseases [1]. Segmentation allows for the identification and counting of WBCs, which is crucial for Various medical diagnostics and research purposes. Figure 1 depicts the microscopic image of blood.

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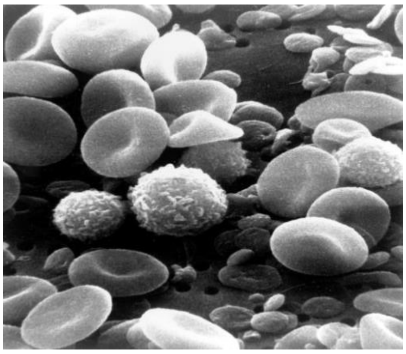

Figure 1. Microscopic Image of Blood

Segmentation is important in enhancing the visibility and analysis of WBCs in the blood images. Machine learning algorithms are particularly useful for separating the cytoplasm from the nucleus of WBCs. These algorithms leverage both spatial and spectral information to accurately distinguish between different regions of interest within the cells, enabling more detailed analysis and improved diagnostic capabilities. Fuzzy C-means clustering, snake algorithm and fusion rules techniques are often used in combination with other image processing and machine learning methods to improve the accuracy and efficiency of leukemia detection and analysis in medical imaging.

2. Related Work

Qing Li et.al.[2] suggested a method to extract as well as identify WBCs in hyperspectral images, enabling detailed analysis and diagnostics in medical applications such as leukemia detection. Yifan Duan [3] aim to achieve accurate segmentation and analysis of leukocytes in hyperspectral images, which can have important applications in medical diagnostics and research by using SMACC technique. Qing Li et.al. [4,5] recommended a technique for identifying WBCs in hyperspectral images using a combined spectral-spatial process. They employed an integrated algorithm that combines spatial k-means with the fuzzy C-means procedure. Qian Huang Et Al [5]. developed a novel framework for blood cell classification that combines Deep Convolutional Neural Network (Deep CNN) Kernels with Modulated Gabor wavelets. Zhou,et.al [6] aimed to enhance the accuracy and efficiency of blood cell analysis, particularly in the context of spectral and spatial feature extraction by using SVM recursive feature elimination. Yuehua Liu et.al [7] addressed two problems related to white blood cell (WBC) analysis which is WBC location and sub-image segmentation.

K.N.Sukhia et.al. [8] aimed to improve the accuracy of WBC detection, especially in cases where cells are overlapped or clustered together, which can be challenging for traditional segmentation methods. S.Ravikumar et.al. [9] focused on the segmentation of WBCs using the standard ELM based classification technique using a fast relevant vector-machine (Fast-RVM) baidyanath shah et.al.[10] focused on extracting the shape of white blood cell (WBC) images to provide outlier features of WBCs. S.Mohapatra et.al. [11] aimed to develop a robust system for the detection and classification of lymphocyte cells, with potential applications in leukemia diagnosis and research. S.H.Rezotofighi et.al. [12] utilized three colors of blood cell images as three independent vectors, which were set as orthonormal. Hayan T.Madhloom et.al.[13] presented a technique used in image processing to enhance and extract features based on the morphology or shape of objects in an image. In [14] the authors utilized global contrast stretching (GCS) and segmentation of white blood cells (WBCs) in HIS (Hue, Intensity, Saturation) color space. Segmentation of WBC by HIS color space. Using this they extract WBC nucleus region by setting some threshold, for all images. In [15] the authors focused on detecting chronic lymphocytic leukemia (CLL) of blood cells. They employed the watershed algorithm, combined with an optimal thresholding technique, to separate normal lymphocytes From CLL lymphocytes.

3. Methodology

Figure 2 illustrates the process of segmentation and preprocessing techniques of WBC image. In first phase the input RGB image is converted into gray scale image. The intensity adjustment techniques are used to image normalization. The gray scale image is fed to the Fuzzy -C means clustering. Based on subjective certainty, the cluster value three is assigned. The Fuzzy C means clustering is an unsupervised learning. The normalized image is fed to the active contour's segmentation techniques. Active contours, often referred to as snakes, are curves or contours that are iteratively drawn over an image domain. These contours evolve over time, influenced by both internal forces from within the contour itself and external forces computed from the image data. The snake algorithm is a process of aligning a deformable model (the snake) to the image by minimizing an energy function. The result obtained from FCM and active contours models are fused by using fusion rule. Finally, the output of model is segmented WBC images.

3.1 Fuzzy C Means Algorithm

The membership function of FCM is given by

$$U_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - c_j\|}{\|x_j - c_k\|}\right)^{\frac{2}{m-1}}} \quad (1)$$

$$The\ centroid\ of\ the\ equation\ is\ given\ by$$

$$C_j = \frac{\sum_{i=1}^{M} U_{ij}^{m} X_i}{\sum_{i=1}^{M} U_{ij}^{m}} \quad (2)$$

$$The\ iteration\ will\ stop\ when\ equation\ 3\ is\ fulfilled$$

$$max_{ij} \left\{ \left| U_{ij}^{(k+1)} - U_{ij}^{(k)} \right| \right\} < \varepsilon \quad (3)$$

Step 1: Initialize U = [U_{ij}] ($U^{(0)}$) “fuzzy partition matrix” using the random numbers generated in the range 0 to 1 wrt Equation 1

$$\sum_{i=1}^{M} \sum_{j=1}^{C} U_{ij} = 1 \quad (4)$$

Step 2: In step *k*: estimate the vector centers $C^{(k)}$ =[c_j]with $U^{(k)}$ using Equation 2.

Step 3: Update $U^{(k)}$, $U^{(K+1)}$ “fuzzy partition matrix” by the new computed U_{ij} according to Equation 3.

Step 4: Calculate the objective function using Equation 3. If the difference across the objective function adjacent values is less compared to criteria to terminate ε stop iteration; else go back to step 2.

3.2 Active Contour (Snake) Algorithm

The snake algorithm, also known as the active contour model or snake model, is a method utilized in image processing and computer vision to detect and track object boundaries within images. The basic steps of the snake algorithm are as follows:

1.Initialization: Start with an initial contour or curve that roughly outlines the object of interest in the image. This contour can be manually defined or generated automatically.

2.Energy Minimization: The snake algorithm iteratively adjusts the contour to minimize an energy function. This energy function typically consists of two components as internal energy and external energy. Internal energy is used to encourages smoothness and regularity of the contour and prevents the contour from deforming excessively. External energy is used to derived from the image itself, this energy attracts the contour towards features such as edges or intensity gradients. It helps the contour align with the object's boundaries.

The contour is iteratively updated to minimize the combined internal and external energies. This is often done using techniques like gradient descent, where the contour is adjusted in the direction that reduces the overall energy. Convergence is one of the processes continues until the contour converges to the object's boundary or until a stopping criterion is met. Once the contour has converged, post-processing steps may be applied to refine the result, such as smoothing the contour or removing small spurious segments. The snake algorithm is flexible and can be adapted to different types of images and objects by adjusting parameters and energy functions

3.3 Fusion Rule

In this work, averaging selection fusion rule is applied. The averaging fusion rule is defined as pixel values of corresponding pixels from different images.

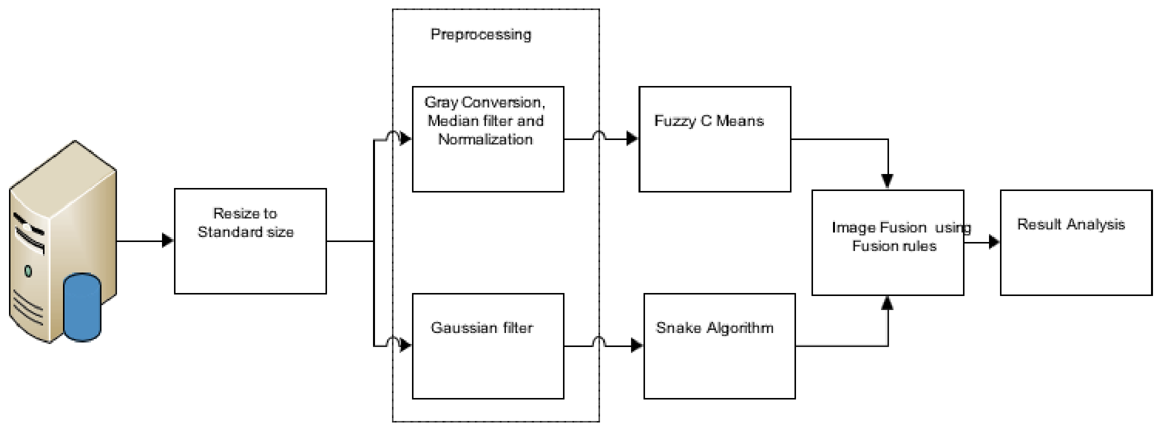

Figure 2. Pre-Processing and Segmentation

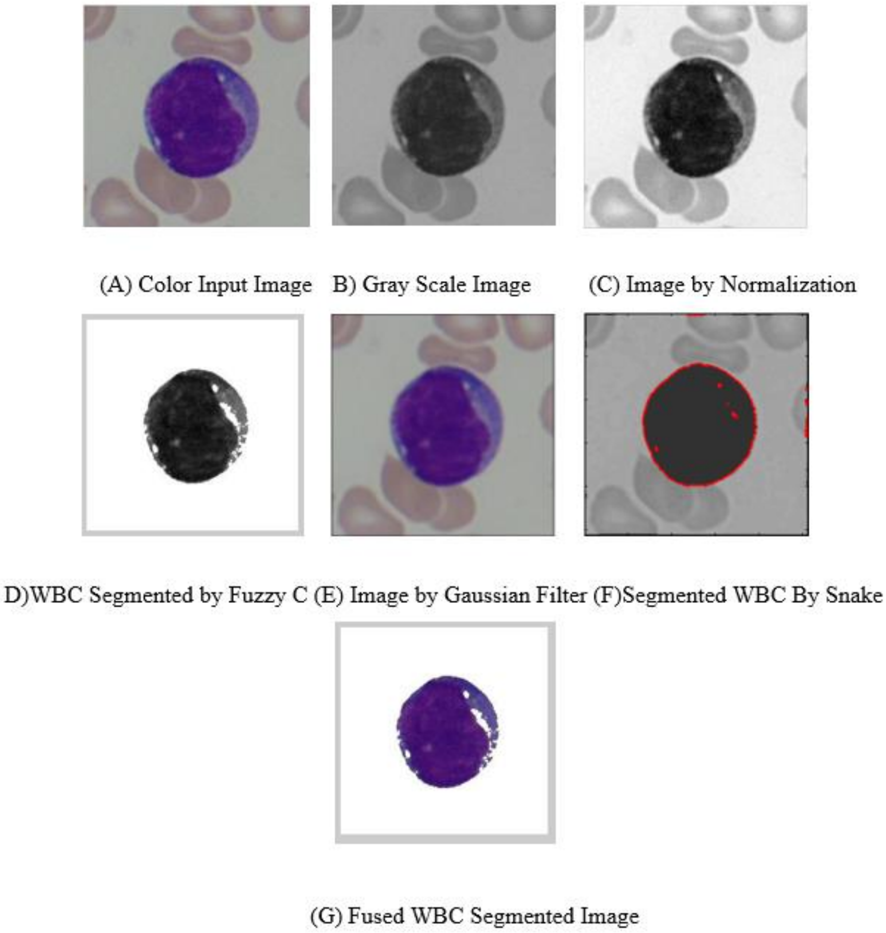

Figure 3. Test Image with Intermediate Results.

3.4 VGG 19 and Mobilenet Version 3

In the first phase of the work, VGG19 transfer learning methods were used to classify the WBC cell. In next part, Mobilenetv3 is a State-of-the-Art CNN architecture designed for efficient and high-performance mobile vision applications. It is a continuation of the mobileNetv3 series, which aims to provide lightweight yet powerful models for various tasks such as image classification, object detection, and semantic segmentation. in this work mobile network version V3 is used for image classification and it builds on the advancements of MobileNetV1 and V2, incorporating novel techniques to improve both speed and accuracy. Figure .4 indicates architecture of MobileNetv3. Table 1 shows parameters of proposed network.

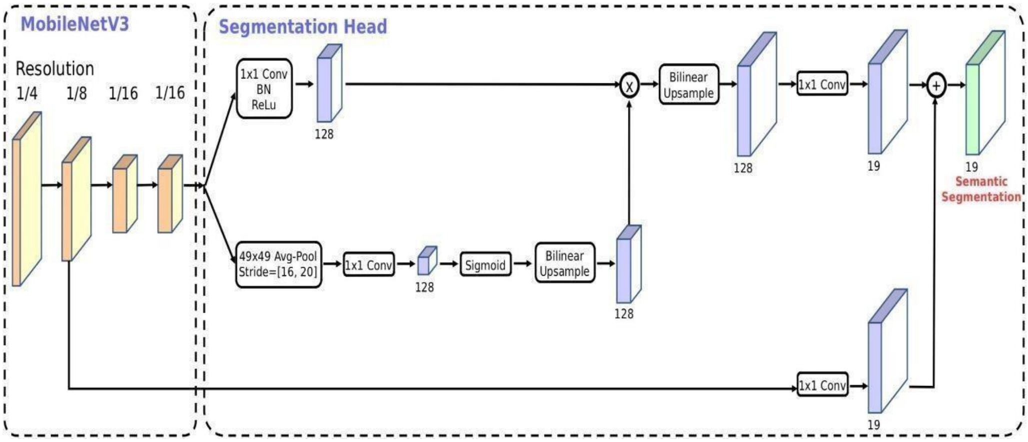

Figure 4. Indicates Architecture of Mobile Net Versionv3

MobileNetV3 represents a balance between computational efficiency and model accuracy, leveraging advanced techniques such as depth wise separable convolutions, SE modules, and neural architecture search. Its development involved significant modifications and optimizations to ensure high performance on mobile and edge devices, with careful consideration of training parameters to achieve optimal results. The hyper tuning parameter of proposed architecture are listed in Table 1. From the Table 1 shows 6,448,676 total parameters, all of which are trainable. It consists of 9 layers, with a softmax activation function used for classification into 4 classes. The model was trained using the Adam optimizer and the sparse categorical cross-entropy loss function for 9 epochs. After training, the model achieved an accuracy of 96% on the validation dataset, with a loss of 0.2.

Table 1. Hyper Tuning Parameters of MobileNetV3

Parameters	Value
Model Sequential Total Params	6,448,676
Trainable Params	6,448,676
Non-trainable params	0
Layers	9
Activation function	softmax
Optimizer	Adam
Loss function	sparse categorical cross entropy

Layer	Dense
Classes	4
Epochs	9
Accuracy	0.96
Loss	0.2

4. Result and Discussion

The table 2 indicates the architecture of Mobilenetv3 compared to VGG 19 architecture. The table presents performance metrics for a model evaluated on two occasions. In the second evaluation, the model showed improvements in accuracy (97.62% to 98.51%), specificity (94.21% to 96.02%), sensitivity (98.02% to 98.95%), and precision (98% to 98.85%) compared to the first evaluation. These improvements indicate that the model's performance increased across various aspects, suggesting its effectiveness in correctly classifying instances and identifying true positives and negatives.

Table 2. Performance Metrics

S.No.	Parameters	VGG 19	MobileNetV3
1	Accuracy	97.62%	98.51%
2	Specificity	94.21%	96.02%
3	Sensitivity	98.02%	98.95%
4	Precision	98%	98.85%

4.1 Train Test Validation

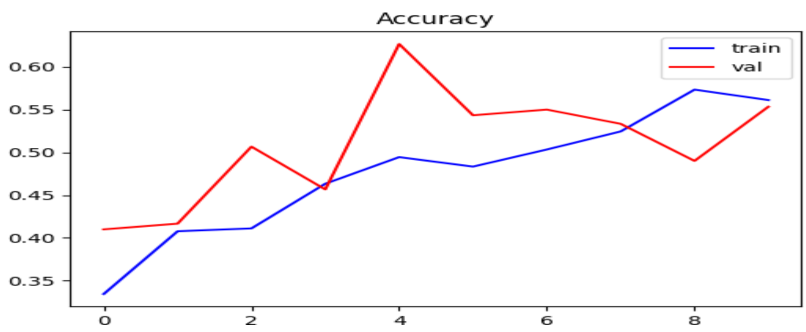

Figure 5. Accuracy

Figure 5 displays the accuracy plot as a function of the number of iterations. It helps identify the iteration point at which the accuracy converges, indicating the point where the model has reached its optimal performance or stability.

5. Conclusion

In this research a technique for automated detection and classification of blood images using Mobilenetv3 is proposed. The image segmentation algorithm Fuzzy C -means clustering snake algorithm and fusion rules has been applied. The accuracy, specificity, sensitivity, and precision of classifier is 98.51%, 96.02%, 98.95%, and 98.85%. Further research will focus on the use of spectral features as essential features for classification.

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