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Leukocytes Classification and Segmentation in Microscopic Blood Smear: A Resource-Aware Healthcare Service in Smart Cities

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ABSTRACT Smart cities are a future reality for municipalities around the world. Healthcare services play a vital role in the transformation of traditional cities into smart cities. In this paper, we present a ubiquitous and quality computer-aided blood analysis service for the detection and counting of white blood cells (WBCs) in blood samples. WBCs also called leukocytes or leucocytes are the cells of the immune system that are involved in protecting the body against both infectious disease and foreign invaders. Analysis of leukocytes provides valuable information to medical specialists, helping them in diagnosing different important hematic diseases, such as AIDS and blood cancer (Leukaemia). However, this task is prone to errors and can be time-consuming. A mobile-cloud-assisted detection and classification of leukocytes from blood smear images can enhance accuracy and speed up the detection of WBCs. In this paper, we propose a smartphone-based cloud-assisted resource aware framework for localization of WBCs within microscopic blood smear images using a trained multi-class ensemble classification mechanism in the cloud. In the proposed framework, nucleus is first segmented, followed by extraction of texture, statistical, and wavelet features. Finally, the detected WBCs are categorized into five classes: basophil, eosinophil, neutrophil, lymphocyte, and monocyte. Experimental results on numerous benchmark databases validate the effectiveness and efficiency of the proposed system in comparison to the other state-of-the-art schemes.

INDEX TERMS Healthcare in smart cities, haematology, image classification, image segmentation, leukocytes classification, mobile-cloud computing, medical image analysis.

I. INTRODUCTION

A smart city transforms traditional health care services into centralized and online services, providing patients ubiquitous access to standard diagnostic services. Moreover, smarter health care management translates health-related data into medical and professional intuitions. Researchers are also working to provide resource-aware e-Health frameworks for data sharing and diagnostically relevant information extraction using mobile-cloud architectures. This empowers the medical specialists to improve the productivity of services provided at the underlying smart environments. In this context, the field of mobile computing has been significantly focused by carrying out extensive research, reducing computational complexity. These mobile-cloud computing frameworks specifically reduce the computation burden in terms of system performance by offloading various tasks to the cloud server from smart phones [1]. Information and communication technologies, particularly mobile-cloud computing, have experienced rapid development, positively impacting our lives in several ways [2]. Mobile-cloud based health telematics is an emerging research area that brings a major improvement with regard to patient subsists, especially in remote areas for the elderly, disabled, and chronic patients. Therefore, rapid development in mobile technology and smartphone based healthcare systems are increasingly becoming useful to deliver health services easily. In smart cities, mobile-cloud plays an important role to facilitate the doctors/haematologists to monitor patients remotely in a very cost effective manner [2]. Similarly, mobile-cloud based leukocytes classification systems can provide eHealth solutions and address hematic diseases including hematic problems such as AIDs and blood cancer (Leukemia) by reducing the existing high costs of national healthcare to cheaper health care solutions. The current demand of this modern technological age is to facilitate the doctors/haematologist in diagnosing hematic related problems remotely and facilitate patients by providing easy access to health facilities in smart cities regardless of time and place. In this context, we present a resource-aware mobile-cloud based framework for leukocytes classification and segmentation in microscopic blood smear images. Leukocytes classification and segmentation provides valuable information to specialists and haematologists in medical diagnostic modalities. Mobile-cloud based medical imaging can allow us to detect and recognize different types of blood cells, soft tissues, and bones from medical images [3]. It has been observed in the medical field that the majority of diseases in the body can be identified by analyzing blood samples. This is evident from different medical imaging softwares, which automatically diagnose various types of diseases by analysing leukocytes [4].

The processing of microscopic blood smear images also helps us to detect RBCs/platelets, count the number of cells, calculate their sizes, and normal percentages in human blood. Leukocytes consist of five sub-categories known as monocyte, lymphocytes, basophile, eosinophil, and neutrophil. In order to diagnose and correctly detect leukocyte and its underlying sub-class, a multi-class classification is considered as the best option, which can be used to efficiently classify each category. To accomplish this task, we first need to detect WBCs in microscopic blood smear images. There are two possible methods to detect WBCs in blood smear images: manual segmentation and automatic segmentation. Manual segmentation of nucleus from WBCs and their classification is based on a pre-defined procedure, which is inherently difficult, prone to errors, and time consuming due to the involvement of human labour. Furthermore, the instruments used by experts for manual segmentation and classification of WBCs are not affordable by all hospitals and clinics, especially in remote areas.

Image classification is based on different image features like histogram of gradients (HOG), edges, geometric, texture, and statistical features [5]. First step in image classification, is pre-processing, which includes image sharpening, contrast adjustment, and noise removal. Different techniques are used for the enhancement of microscopic images. The enhanced image is further processed for segmentation of WBCs using different segmentation techniques such as manual thresholding [6], OTSU binarization, fuzzy c-means (FCM) [7], and active contours [8]. Active contours are well-known segmentation algorithms and are widely used in various applications such as medical image analysis and computer vision. Active contour models segment the objects from an image using curves, which start around the object and move toward its inner normal. When it reaches the boundary of the segmented object, it stops moving. From the stopping point, shape of the object is detected [9]. FCM is unsupervised clustering technique which is frequently used in image segmentation, allowing a chunk of data belong to two or more clusters [10].

In the proposed work, K-means is used which is an automatic segmentation algorithm whose speed depends on the number of clusters K. According to this approach, similar intensities are clustered in the same class while different intensities are clustered to other classes based on the value of K, which is selected manually. The proposed framework segments the WBCs into four clusters. Firstly, the enhanced RGB image is converted to HSI color model. Color K-means is used to extract leukocyte from the blood smear image. Next, features from the segmented WBC are classified using support vector machine (SVM). The extracted features include: 1) statistical features such as mean, variance, standard deviation, root mean square (RMS), regression, skewness, and kurtosis, 2) texture features such as correlation, gray level co-occurrence matrix (GLCM), entropy, energy, and inverse difference moment, which are extracted from 300 different types of WBCs. The proposed framework claims following major contributions:

1) A novel smartphone based cloud assisted system is proposed for leukocytes classification and segmentation in blood smear images, helping haematologist in diagnosing various diseases more efficiently with better accuracy. To this end, our system provides citizens fast and easy access to quality healthcare service anytime/anywhere and enable medical specialists to monitor and make timely decisions about abnormal findings in target population in smart cities.
2) Reduce internet bandwidth cost by offloading image features to the cloud to train a multi-class classifier, instead of sending an entire diagnostic image dataset.
3) For efficient and effective segmentation, a color K-means clustering algorithm is incorporated into the proposed framework, providing better segmentation results compared to other state-of-the-art schemes.

The rest of the paper is structured as follows: Section II reviews the current literature of leukocytes segmentation and classification. The proposed work is explained in Section III. Experimental results and conclusion are given in Section IV and Section V, respectively.

II. LITERATURE REVIEW

This section provides review of related current state-of-the-art schemes for leukocytes segmentation and classification. In recent years, various medical applications such as mobile healthcare, remote patient monitoring, and tele-endoscopy services have been developed in smart cities, utilizing mobile-cloud resource rich framework [11]. The gradual advancements of techniques for leukocytes segmentation and classification have been accessible to explore their role in medical filed, because leukocytes segmentation and classification plays a dynamic role in medical hematology to diagnose different hematic pathologies.

A. COMPUTER-ASSISTED LEUKOCYTES SEGMENTATION AND CLASSIFICATION APPLICATIONS

Leukocytes segmentation is used in medical imaging to study the anatomical structure, diagnosis, treatment planning, and locate tumours. Ravikumar [12] presented a segmentation method using thresholding and ellipse-curve fitting. They used morphological properties for feature extraction, followed by classification of leukocytes using a naïve Bayes classifier. They utilized both geometrical and statistical features for classification purpose. The method is tested on two different datasets and the results were compared with other WBCs classification techniques. Rezatofighi *et al.* [8] presented framework to automatically segment five types of WBCs using a gran-Schmidt ortogonalization method in combination with snake algorithm. For this purpose, they extracted texture features from blood smear images. Two classifiers including artificial neural network (ANN) and SVM were tested and a comparative analysis was performed based on their classification performance.

Ko *et al.* [13] leukocyte from images using merging rules based on mean shift clustering and boundary remover rules. Gradient vector flow (GVF) [14] was used for segmenting nuclei and cytoplasm. For nuclei segmentation, probability density function was estimated from WBC nuclei. Mean shift clustering was used to segment the nuclei while cytoplasm was segmented using morphological opening of the green channel of RGB. Boundary edges and noise were removed by the GVF method to detect cytoplasm boundaries. Sholeh [15] used different algorithms for WBC enhancement and segmentation. Platelets and noise were removed from blood smear images using morphological operations. To smooth the cell shape, opening and closing operations were performed. Segmentation of WBC was done by obtaining the blue channel. Next, the five types of WBCs were segmented, counted, and classified. Then, the segmented image was labelled for leukocytes counting, followed by features extraction such as major axis length, minor axis length, and average axis length. Finally, ANN was used to automatically classify the five types of WBCs.

Prinyakupt and Pluempitiwiriyawej [3] have used thresholding and mathematical morphology for segmentation of cell nucleus. Morphology is a mathematical operation that applies addition/subtraction on blood smear images to separate WBCs, RBCs, and platelets. Threshold segmentation was done to partition the image into background and foreground and the optimal threshold value for the segmentation of WBCs was then selected. Geometrical features were extracted and SVM classifier was used for classification of leukocytes. In another study [16], self-dual multi-scale morphological toggle method was used to segment the nucleus and cytoplasm of WBCs. Watershed transform and level set methods were used to identify the cytoplasm regions. For identification of cytoplasm, there are two different techniques based on granulometric analysis and morphological transformations. This method extracted geometrical features such as area, solidity, eccentricity, perimeter area of convex part of the nucleus, ellipse, and its major axis length. Authors used KNN classifier for the classification of WBCs.

In [17], different segmentation techniques have been used such as global thresholding and FCM, calculating the blue channel of blood smear images for segmenting WBCs. Next, stain colour analysis is performed to get the feature vector of a particular region of interest. Finally, leukocytes are classified as infected or non-infected according to the set threshold value of the dataset. Bikhet *et al.* [17] enhanced the input image by removing noise and subtracted the foreground. Next, different features such as area of the cell, area of the cytoplasm, area of the nucleus and average colour of the cell were extracted for classification.

Ravikumar [12] conducted a comparative study of two techniques known as standard extreme learning machine (ELM) classification technique and fast relevance vector machine (FRVM) for segmentation. In comparison to FRVM, ELM classification technique performs well in local maxima. However, overall performance of ELM is not satisfactory [12]. To overcome the limitations of ELM and FRVM, authors modified the FRVM, which effectively detected leukocytes. Sedat Nazlibilek *et al.* [18] presented another approach which applies image enhancement on blood smear images prior to segmentation of WBCs using Otsu segmentation algorithm. Then, a set of morphological operations were used for removing unwanted objects and filling the holes. Next, the size of each segmented cell was calculated by using geometric features such as major axis length, minor axis length, and average axis length for each segmented object followed by classification of leukocytes into different classes using neural network. Piuri and Scotti [19] followed a similar approach as devised by Sedat Nazlibilek *et al.* [18]. However, they used feed-forward neural networks classifier for classification.

The aforementioned methods have two major issues: they are computationally expensive and their accuracy rate decrease drastically when tested on real datasets having noise and light reflectance. Keeping in view the above challenges, we have presented a resource-aware leukocyte classification and segmentation framework, offloading computationally complex tasks from smartphones to cloud server. However, analysis of blood sample images with mobile-assisted health monitoring systems is challenging due to limited resources of smart devices for data processing and transmission. To overcome this issue, we proposed an efficient and adaptive offloading framework for utilizing the available resources considering users' preferences.

B. MOBILE-CLOUD COMPUTING IN MEDICAL APPLICATIONS

In recent years, mobile-cloud computing has become a valuable area for researchers [2], [20], mainly focusing to minimize the computational burden on smart devices by offloading computational tasks to cloud server, extending lifespan of smart devices. Guet *et al.* [21] have done extensive trace-driven assessments that presented efficient offloading extrapolation machines that can effectively reduce resource limitations of smartphone devices to minimize computational burden than other common schemes. Yang *et al.* [22] showed a resource-aware offloading scheme for a resource constrained smartphone devices. They focused the overall resources of the system including computational power, storage, and communication cost. Main purpose of the system was to save valuable resources up to greater extent. Miettinen and Nurminen [23] described energy consumption as a secondary source for smartphones. Hashem *et al.* [24] have given an extensive review of mobile-cloud computing in the field of mobile-cloud based healthcare. They aided various state-of-the-art methods dictating the constraints of the currently developed approaches. Utilization of cloud computing is mandatory, because most of the image processing techniques required high computational power, storage space, and network bandwidth. Liu *et al.* [25] presented an adaptive resource discovery based energy-efficient technique for mobile cloud computing which works independently with different network environments.

III. METHODOLOGY

Mobile-cloud based leukocytes segmentation and classification is an advanced technology and through this, system specialists and haematologists can easily diagnose different haematic's locally and remotely. Mobile-cloud based leukocytes classification and segmentation can be performed either on local devices or at cloud. The proposed system will help doctors and haematologists to access blood microscopic images from the database for processing, sharing, and analysis. However, the implementation of such type of framework on mobile device is challenging task due to its limited resources in terms of computational power and storage. Therefore, we combine mobile and cloud computing because it provides better computational speed, storage, and communication services in a scalable way at low cost. The proposed framework is the extended version of our previous work [26] which consists of three modules: (1) mobile-cloud with a reliable communication system to access main haematology database; (2) WBCs segmentation and classification of microscopic blood smear images through offloading from mobile to the cloud; (3) cloud server for processing and delivering secure storage and provide access to their authorized users to utilize different image processing and machine learning. Overview of the proposed resource-aware framework is shown in Fig. 1.

Input blood smear image is first processed to segment nuclei and then different features are extracted from the segmented nuclei for the purpose of training multi-class classifier in the cloud. Trained classifier is used for WBCs classification. This will facilitate the doctors and haematologists to remotely perform haematics related tests anytime without carrying heavy instruments. Features are extracted locally from the microscopic blood smear images, and offloaded to cloud server for further analysis. The trained multi-class classifier model is registered in the cloud. This enables the specialists to access the cloud based trained classifier model for classifying leukocytes into their respective categories from microscopic blood smear images through their mobile devices. Trained model and processed images can be stored on cloud server for future usage.

A. MOBILE-CLOUD BASED LEUKOCYTES CLASSIFICATION

Current mobiles have limited potential and are not applicable to process complex tasks. Thus, the leukocytes classification and segmentation from microscopic blood smear images is a computationally challenging task and such kind of tasks can be transferred to cloud server for processing. For offloading, a virtual machine (VM) based learning technique is used that can ensure the ability by transferring computationally heavy tasks partially or entirely from a mobile to more prevailing servers such as cloud server [27]. For leukocytes classification and segmentation, a multi-class classifier is trained in the cloud.

B. OFFLOADING-BASED LEARNING AUTOMATA

Learning automata in context of mobile-cloud offloading is an adaptive decision making model, which interacts with surrounding environments in discrete time instants. At each time instant, the proposed automata chooses a suitable threshold value for partitioning data and its processing tasks into local and cloud server. Data collected from environment works as an input for the learning automata and therefore it is known as response from the environment. In the underlying scenario, automata gets responses from surrounding environment, i.e., computational power, storage, bandwidth, and battery strength of a mobile phone, and then it shows special reaction (threshold calculation) in that specific situation. The process of threshold selection based on environment parameters is called reinforcement. The variation in the performance of the mobile-cloud adaptive loading framework is termed as ''learning'', and, therefore, the learning system enhances the performance with respect to time in the process of achieving ultimate goal i.e., ideal threshold value selection. There are various internal and external environmental conditions that can increase or decrease the performance of the proposed learning technique. The proposed learning automata can be represented as LE = {A, B, C}, where A is input set, B is output set and C represent the environment as shown in Fig. 2.

C. MOBILE DEVICE RESOURCE MONITORING

Prior to data offloading, it is required to analyse the resources consumption of mobile device. Learning automata-based offloading continuously tracks device resources such as computation power, storage, battery consumption, and internet bandwidth. In mobile-cloud based healthcare, smartphone devices send and receive the data/information over continuously varying network bandwidths. Variation in the internet bandwidth can affect overall performance of the system by

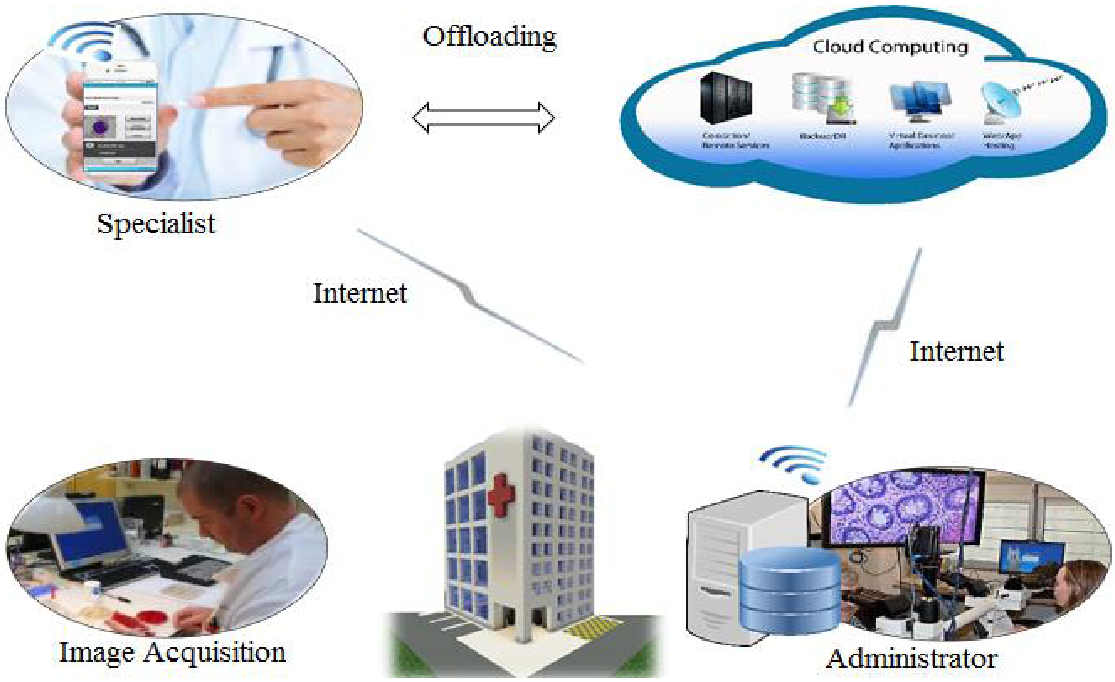

FIGURE 1. **Proposed mobile-cloud assisted leukocytes segmentation and classification framework.**

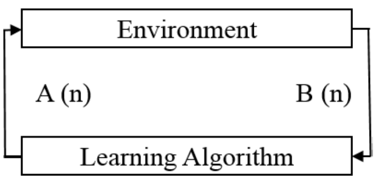

FIGURE 2. **Illustrating the relationship between learning algorithm and environment.**

disrupting the smooth transmission of patient data to cloud server. In the proposed framework, communication is the main element that needs to adjust according to the situation in order to save energy consumption of the computational method [28]. Optimal data offloading between mobile device and cloud sever is fully dependent on the bandwidth of the network. The device resource monitoring unit of the proposed framework evaluates the available communication resources and the resources required to offload data for further processing in the cloud.

D. TRAINING OF MULTI-CLASS CLASSIFIER IN THE CLOUD

Machine learning algorithms generally require large amounts of system resources such as computation power and storage. Machine learning techniques need large amount of training datasets for getting better accuracy [29]. However, large training dataset cannot be loaded into mobile memory in the training phase, due to limited storage space and limited computational resources. Therefore, it is required to offload the diagnostic data to cloud, reducing computational and storage burdens on a mobile device. In machine learning field, some classifiers offer more robust and accurate classification procedures due to their global properties such as ANN [30] and SVM [31], [32]. These techniques become more complex and expensive to process large datasets on smartphone [33]. In current technological era, there are various distributed machine learning methods which can be trained on multiple local computers or on single powerful cloud server. Once trained, these models can be used for testing purposes on both local as well as remote locations. Hence, we propose a resource-aware training model to train a classifier on ubiquitous cloud server.

Cloud-based classifier training mechanism with MapReduce technique is shown in Fig. 3. MapReduce is a programming model build up on the concept of functional programming called map and reduce function [34]. The MapReduce model is widely used to reduce classifier training time for processing heavy datasets, dealing both heterogeneity and large scale data. Similarly, a multi-class classifier can be trained on cloud server. Performance of this model is important, particularly in computational expensive tasks such as machine learning applications [29].

E. CLOUD SERVICE

In mobile-cloud based leukocytes segmentation and classification from microscopic blood smear images, hematologists are provided detailed and broad evidence to correctly diagnosis different diseases. Cloud provides global access for storing, retrieving data, and performing data analysis in more easy and secure way.

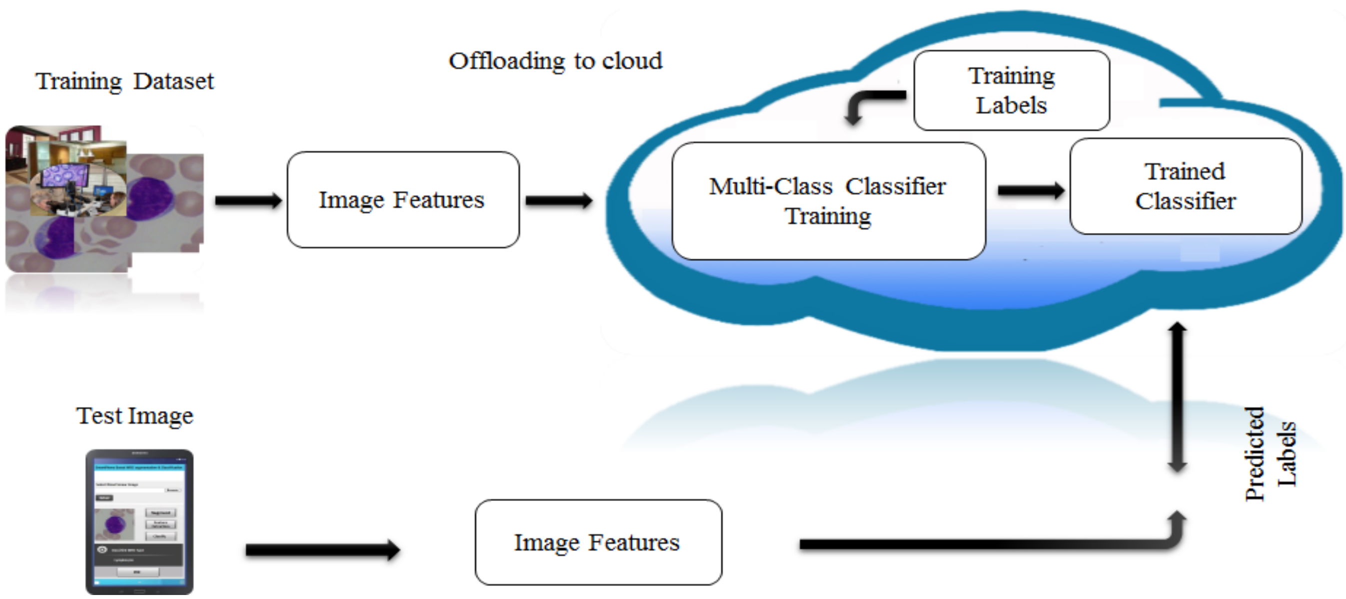

FIGURE 3. **Training a multi-class classifier on a cloud server.**

For instance, in WBCs classification based on mobile-cloud, we only need to train a multi-class classifier in the cloud in order to classify WBCs, producing precise results for medical specialists and hematologists. There are number of cloud service providers such as Microsoft, Apple, Amazon, and Google [35]. For simulation purpose, we selected Google App Engine[1] (GAP), because it provides definite features to their clients in a cost effective manner. GAP is more suitable for Android based mobile devices as it uses secure plug layer to provide high-level security for encoding its different services [36]. It also facilitates users by providing an option to set up their privileges based on the interfaces assigned to them. Therefore, the security and privacy of the client's data and application is ensured by Google [37]. Moreover, it provides free services to its user for prototyping.

IV. MOBILE-CLOUD ASSISTED LEUKOCYTE ANALYSIS

In this section, the proposed resource aware framework for leukocytes classification and segmentation is explained. The framework consists of three steps: 1) WBC's nuclei segmentation from microscopic blood smear images, 2) features extraction from the segmented nuclei, and 3) training of multi-class classifier model on cloud through extracted features for classification of leukocytes into their respective five categories. Segmentation is performed using a colour K-means clustering algorithm. After segmentation, the segmented region is transformed to the frequency domain, where a set of statistical and textural features are extracted. For effective and resource- conscious classification, a mobile-cloud assisted multi-class ensemble classification scheme is trained on cloud. The proposed framework has the capability to easily segment and classify WBCs into their corresponding five classes. Fig. 4 describes the schematic representation of the proposed segmentation and classification framework.

A. DATA ACQUISITION AND PRE-PROCESSING

The study consists of 1030 blood smear WBC samples which were collected from Hayatabad Medical Complex (HMC[2]) Peshawar, Pakistan. These blood smears were captured with Head Nikon DS-Fi2 [3]having high-definition color. The digital images were taken with approximately 100× magnification factor. All the images were saved in JPG format of dimension 960 × 1080 pixels.

The size of the images was adjusted to 256 × 256 pixels during processing in MATLB as per the requirements of simulation. The detail of the dataset is given in Table 1. Blood smear enhancement includes noise removal, contrast adjustment, and image sharpening. In the underlying work, the acquired images are sharpened using a Gaussian un-sharp mask because sharp images can be easily segmented [38]. In the proposed method, the sharper images are converted from RGB to HSI colour space for applying the colour K-means clustering algorithm [15]. The main purpose of converting RGB colour space to HSI is to minimize the number of colours, helping in easy segmentation of WBCs using the K-means clustering algorithm [39].

B. BLOOD CELLS NUCLEI SEGMENTATION

In image processing and machine learning applications, image segmentation presents division of areas having similar properties. Through image segmentation, a given image can

[1]https://cloud.google.com/appengine/docs

[2]http://www.hmcpeshawar.com.pk/

[3]https://www.nikoninstruments.com/Products/Cameras/Camera-Heads/DS-Fi2

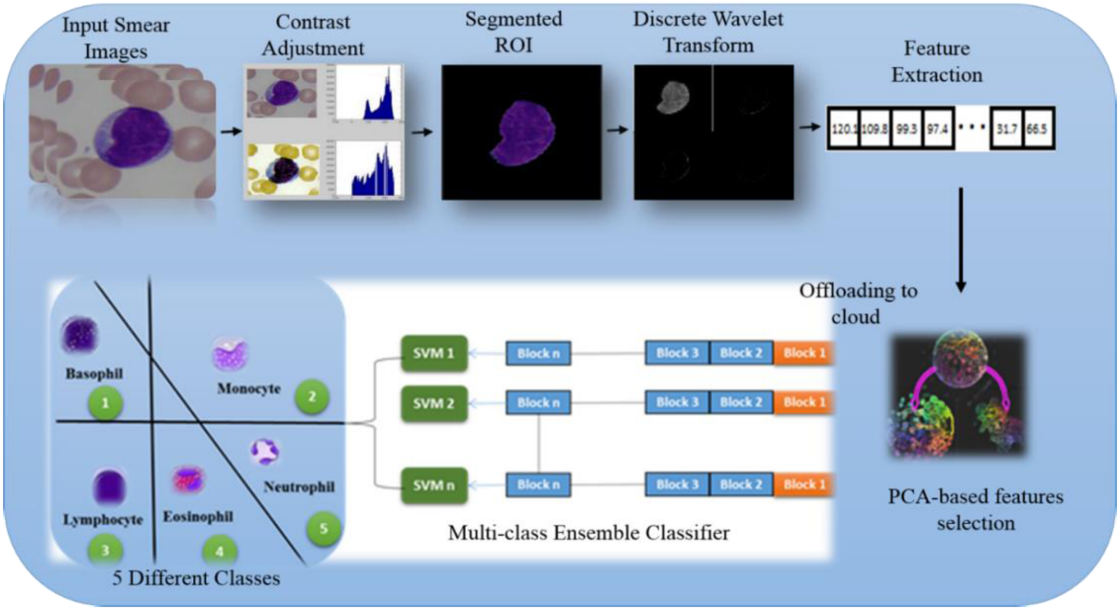

FIGURE 4. Proposed leukocytes segmentation and classification framework.

TABLE 1. Image dataset obtained from HMC hospital.

Type	Basophil	Eosinophil	Lymphocyte	Monocyte	Neutrophil	Total
No of Images	60	90	350	380	150	1030

be converted into a meaningful form for further analysis [10]. Image segmentation has numerous practical applications in different fields, especially in medical imagining such as studying the anatomical structures, diagnosis, treatment planning, localizing tumours, counting leukocytes, classifying WBCs, and other pathologies. Image segmentation refers to the partitions of an image into a set of disjointed and similar regions, which are meaningful to a particular application [40]. Thus, the segmentation process is based on global thresholding, mathematical morphology, FCM clustering, watershed, Otsu binarization, and colour contrast. Global thresholding is a better option to segment microscopic blood smear images. However, cytoplasm, nucleus, and background have their own unique grey levels. Thus, global thresholding can perform worse when the lighting level varies from one image to another image. Colour based segmentation of WBCs includes five different techniques to segment them from other cells of the image. The user can select one of these methods and check the precision and accuracy of different techniques to decide the correct algorithm for a particular application and disease. In order to select the suitable segmentation method for the proposed framework, we considered K-means cluster based segmentation, FCM, active contours, watershed method, OTSO and simple thresholding method. Through experiments, we found colour K-means to be the best candidate for the underlying tasks as it is simple and comparatively more accurate for colour based segmentation as shown in Fig. 5.

C. FEATURES EXTRACTION AND FEATURE REDUCTION USING PCA

After the segmentation process, next step is to extract the features, which is critical step towards classification accuracy. Features are descriptors of an image, representing their natural similarities. These features along with their labels are then used by the classifier for matching different images and classifying them into certain classes.

In the proposed work, we have extracted three different sets of features including:

i. Geometric features of an image, i.e., area, circularity, perimeter, and centroid.
ii. Statistical properties such as arithmetic mean, variance, standard deviation, regression, correlation, skewness, kurtosis, root mean square, and histogram.
iii. Textural features such as correlation, energy, entropy, contrast, and inverse difference movement.

These features are extracted from frequency domain, which is comparatively more suitable to extract strong features for leukocytes classification than spatial domain. To this end, DWT is applied on each dimension of the 2D blood images, producing four sub-bands LL, LH, HH, and HL. The process is repeated two times for LL band.

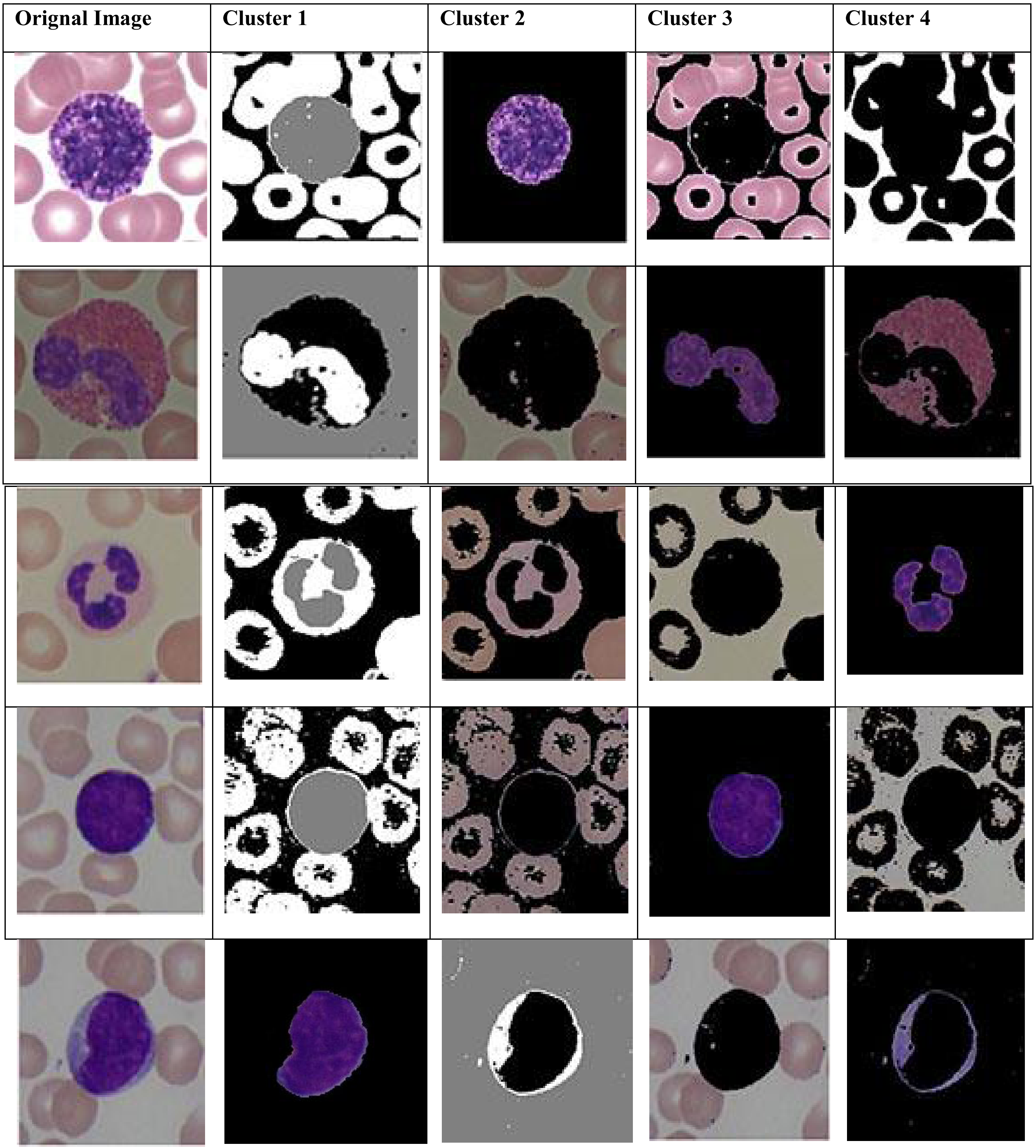

FIGURE 5. Applying K-mean clustering algorithm on blood smear image.

The proposed method uses level-3 decomposition for feature extraction due to statistically rich features of LL band at level-3 of DWT. After features extraction, it is necessary to reduce its size to minimize the computation time and storage requirement. To achieve this goal, a method known as principle component analysis (PCA) is used. PCA is simple and more suitable for our framework compared to other dimensionality reduction methods such as auto encoder, which is its main motivational reason of its usage.

D. MULTI-CLASS SVM-DRIVEN LEUKOCYTES CLASSIFICATION

The next step after feature extraction is selection of the best classifier, considering the input and its expected result. SVM is a well-known supervised learning technique in machine learning, which is based on statistical learning theory. This technique is robust and accurate even if we have a small amount of training data. SVM is a binary classifier but it can be extended further for multi-class classification.

TABLE 2. Comparative analysis of different segmentation methods.

Type	Neutrophil	Lymphocyte	Monocyte	Eosinophil	Basophil	Average
False Positive Ratio (FPR)	0.002	0.002	0.000	0.132	0.002	0.0276
False Negative Ratio (FNR)	0.095	0.045	0.109	0.098	0.095	0.0884
F- Measure	0.872	0.981	0.953	0.872	0.961	0.757

In the proposed work, we have used an ensemble multi-class SVM (EMC-SVM) for classification of leukocytes into its five classes. This is due to the diversity of blood smear images for which training a single classifier is impractical because of limited performance [11], [13]. It has been experimentally proven that ensemble SVM performs well compared to traditional SVM [41]. Therefore, the proposed EMC-SVM was devised to classify the WBCs into five different classes. For training purposes, 70% of the whole data is utilized. The remaining 30% of the data is used for testing the accuracy of the proposed classifier. To test a new blood smear image, same procedure of pre-processing, segmentation, and feature extraction is performed. The extracted feature vector is then passed through EMC-SVM, which assigns a class label to the given test image among the available five classes.

V. EXPERIMENTAL EVALUATION, RESULTS, AND DISCUSSION

The dataset of white blood smear images used in the experiments is collected from HMC. MATLAB is used as a simulation tool in the proposed system. To collect the ground truth data, four haematology experts were requested to manually classify the WBCs into their corresponding classes, i.e., neutrophils, basophils, eosinophils, lymphocytes, and monocytes. These manual results were recorded to build up the database to estimate the results of different classification techniques. The experiment was conducted on 1030 blood smear images, containing both RBCs and WBCs. From the given dataset, only the WBCs were segmented and classified into their respective classes. The results were then compared with the ground truth to calculate the accuracy of the proposed leukocytes classification technique.

A. SUBJECTIVE EVALUATION OF THE PROPOSED SEGMENTATION METHOD

The subjective analyses are carried out to evaluate the performance of the proposed WBC boundary detection scheme by comparing with the boundary of WBCs marked by a group of medical specialists. Four haematologists were requested from HMC to join digital image processing laboratory for evaluation purposes. These haematologists having experience of more than 10 years in analysing haematological problems. The leukocytes were particularly segmented for diagnostic purpose (having a clear view of their nuclei structure and color). The proposed technique is compared with the ground truth. This algorithm can find and segment the five classes of leukocytes correctly. Evaluation of the proposed segmentation technique is based on three metrics including false positive rate (FPR), false negative rate (FNR) and F- measure which can be computed as follows:

$$FPR = \frac{FP}{TN + FP} \tag{1}$$

$$FNR = \frac{FN}{TP + FN} \tag{2}$$

$$F - Measure = 2 * \left(\frac{FPR * FNR}{FPR * FNR}\right) \tag{3}$$

Where

- True positive (TP) is the number of WBC pixels correctly identified.
- False positive (FP) is the number of non-WBC cells pixels that are marked as WBC pixels.
- True negative (TN) refers to the number of non-WBC pixels that are correctly marked.
- False negative (FN) is the number of WBC pixels incorrectly labelled as non-WBC
- F-Measure is the weighted harmonic mean of FPR and FNR that provides a more realistic performance scenario of any subjective evaluation method.

In our case, subjective evaluation of the proposed segmentation method in terms of FPR, FNR, and F-measure is given in Table 2. It can be seen that F-measure of the proposed technique for 1030 blood smear images with all types of WBCs in both nucleus and cell segmentations has above 82% value, indicating efficient segmentation results closer to manual segmentation.

B. COMPARATIVE ANALYSIS OF THE PROPOSED SEGMENTATION METHOD

In this sub-section, we evaluated the performance of the K-mean with different state-of-the-art segmentation methods. In the assessment process, we applied the proposed technique individually to each of 1030 blood smear images and results are compared with state-of-the-art segmentation techniques. The proposed segmentation method achieved an average accuracy of 95.7% for nuclei and 91.3% for cytoplasm. Table 3 shows the experimental observations, where correctly detected leukocytes ratio is represented by A_1 as given in Eq. 4. $A_1 = 1$ indicates that all the leukocytes are correctly detected in the microscopic blood smear images. In the evaluation setup, the ratio of the detected leukocytes to the total detected leukocytes is denoted by parameter A_2 as given in Eq. 5. $A_2 = 1$ shows that no incorrect detection occurred. Thus, by analysing A_1 and A_2, we can evaluate the overall

TABLE 3. Performance evaluation with and without colour adjustment in percentage.

Parameter	Without Colour Adjustment	With Colour Adjustment
A_1	90.2	94.6
A_2	89.4	95.1

TABLE 4. Performance analysis of the proposed method, adaptive threshold and active contour-based segmentation method for each type of leukocyte.

Method	Neutrophil	Lymphocyte	Monocyte	Eosinophil	Basophil	Average
Adaptive Threshold-based method [12]	88.7	90.1	92.3	87.2	83.9	88.4
Active-contour-based method [14]	91.9	94.6	94.5	88.3	86.2	91.1
Proposed method	97.6	97.0	97.8	89.4	89.7	94.3

accuracy of the proposed technique. Overall evaluation shows that the accuracy of the proposed technique is much better than other methods. Table 3 shows the effect of colour adjustment on the segmentation performance. The performance of the proposed method is compared with three state-of-the-art methods as shown in Table 4. In case of eosinophil segmentation, accuracy of adaptive threshold-based method is 87.2 which is higher than accuracy of active contour-based method. However, average accuracy of adaptive threshold-based method is lower than active contour-based segmentation method. On other perspective, accuracy of the proposed segmentation method surpasses the accuracy of both active contour-based and adaptive threshold-based segmentation methods in all five categories. Average accuracy of the proposed segmentation method is 94.3 which is greater than the average accuracy of other two underlying comparison methods.

$$A_1 = \frac{The\ number\ of\ currectly\ segmented\ WBCs}{Totlatl\ number\ of\ segmented\ WBCs} X100\% \tag{4}$$

$$A_2 = \frac{Totlatl\ number\ of\ segmented\ WBCs}{Total\ number\ of\ WBCs\ that\ exists\ in\ all\ images} X100 \tag{5}$$

C. QUALITATIVE ANALYSIS BASED ON VISUAL RESULTS

Comparative analysis of visual results of the proposed segmentation technique with two state-of-the-art methods including adaptive thresholding [9] and active contour technique [42] is presented in this section. For this purpose, three parameters were considered to check the visual quality of different leukocytes. The parameters are shape, size, color, and texture. The segmentation method must retain size and shape of the nuclei in the blood smear image. In terms of colors, leukocyte's nuclei and cytoplasm luminance information must be well-preserved in blood smear image. Segmentation technique must have the ability to maintain textures from input blood smear images. Texture regions must not be shown clear by the segmentation technique because the haematologist differentiates some of the leukocytes classes through their texture. Sample qualitative evaluation results are shown in Fig. 6, where first column shows the original blood smear images, second column represents adaptive threshold, third column refers to active contour, and the last column illustrates the visual results for the proposed method.

D. ENERGY CONSUMPTION ESTIMATION MODEL

Energy consumption of a system is defined as the total resource usage by the device from start to the completion of the required task. Energy consumed during a particular task depends on computational complexity of the underlying tasks [43]. In the proposed framework, energy consumption can be analysed in two different scenarios, i.e., energy consumption via local computation and offloading the task fully or partially to cloud sever.

We determined that cloud-assisted applications consume most of the energy in communication process. For smart devices, major factor affecting energy consumption includes energy consumption for process execution (energy consumption per-operation) [44]. In the communication perspective, energy consumption refers to energy required for data transmission (either full-offloading or partial offloading to cloud). Moreover, for smart devices, reliable network connection and transmission energy is required for offloading patient data for testing and receiving classification/decision results from cloud server.

Each of these energy consumption metrics $E_{\textbf{no off}}$ and $E_{\textbf{off}}$ can be calculated as follows:

$$E_{\text{no off}} = \left(\frac{D_{out}}{b'\text{send}} * \text{esend}\right) + \left(e_{Mcomp} * I\right) \tag{6}$$

$$E_{\text{off}} = \left(\frac{D_{inp}}{b_{send}} * \text{esend}\right) + \left(\frac{D_{out}}{b_{receive}} * e_{receive}\right) \tag{7}$$

Herein, $E_{\textbf{no off}}$ refers to local processing without sending data to cloud. In this scenario, most of the energy is consumed during data processing. On the other hand, $E_{\textbf{off}}$ refers to mobile-cloud computing framework, in which data is adaptively offloaded to cloud and computationally expensive task are performed at the cloud server.

Details of each parameter is given in Table 5. Two scenarios are evaluated that whether $\mathbf{E_{total}}$, is positive or negative as given in Eq. 8. This helped in deciding about the execution of the program on mobile device or on cloud server, considering

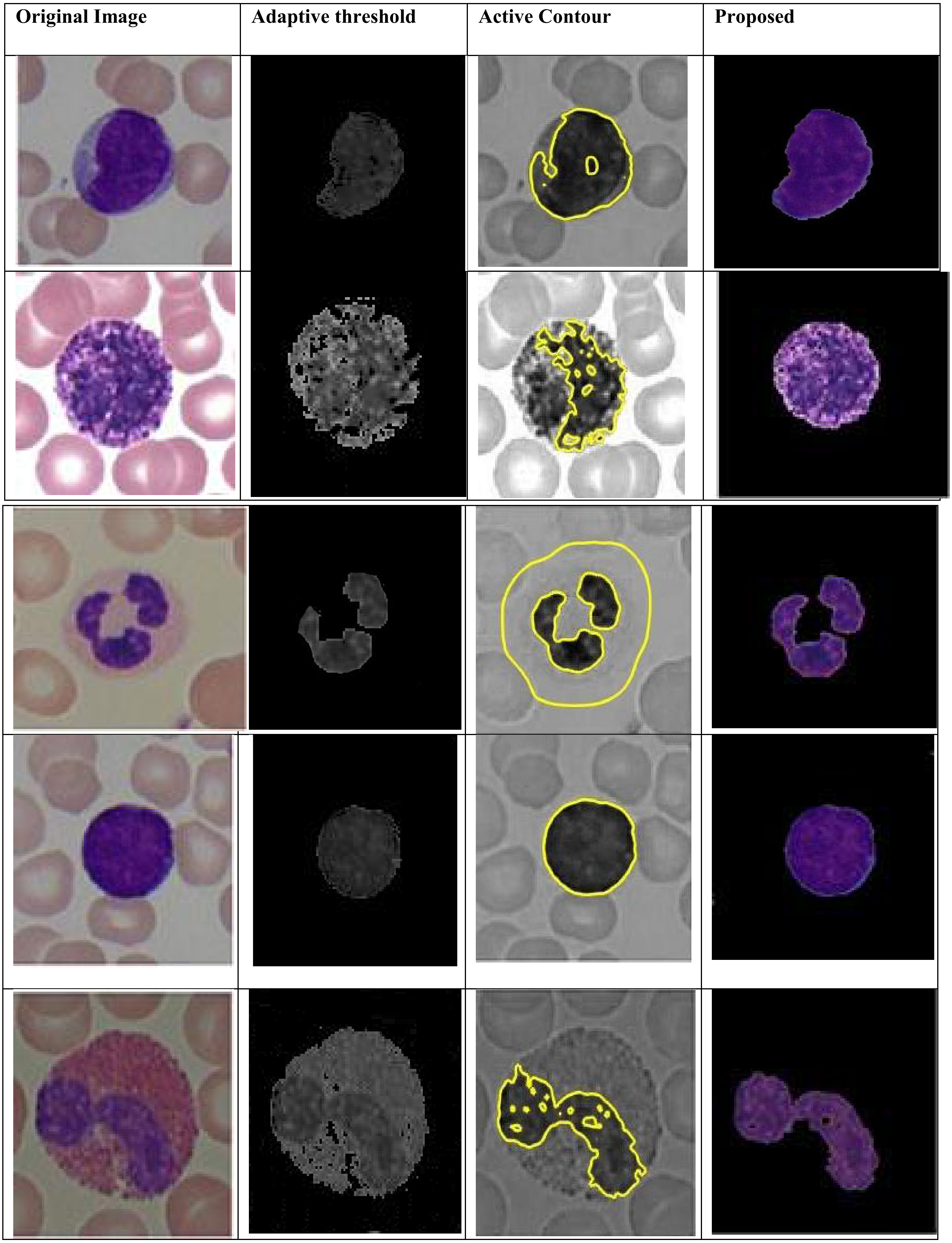

FIGURE 6. Comparative analysis of the proposed method for leukocytes segmentation with adaptive thresholding and active contour model.

TABLE 5. Variables used in the equations.

Variable	Descriptions
D_{inp}	Input data (microscopic blood smear images)
D_{out}	Output data (Class labels)
b_{send}	Required bandwidth for data transmission from mobile to cloud
$b_{receive}$	Required bandwidth for collecting classification results from cloud
b'_{send}	Required bandwidth for collecting labeled data from cloud
e_{send}	Energy consumption (transmitting data from mobile to cloud)
$e_{receive}$	Energy consumption (transmitting data from cloud to mobile)
$E_{Mcomput}$	Energy consumption (implementing program locally in mobile device)
I	Number of instructions (application code)
E_{Total}	Energy difference between mobile and cloud
A, B, R	Reward, penalty, and action parameter

TABLE 6. Approximate energy consumption (in Joules) for both smartphone and cloud server during our mobile-cloud based leukocytes segmentation and classification for three computational scenarios: (1) local computation; (2) entire image-offloading, and (3) Offloading image features.

Computational blocks of the proposed system	Computational Scenarios					
	Smartphone/local processing		Offloading entire image		Offloading image features	
	Time (sec)	Energy (Joule)	Time (sec)	Energy (Joule)	Time (sec)	Energy (Joule)
Pre-processing	3.467	60	3.467	40	3.467	60
Segmentation	1.329	2980	1.0	1980	1.329	2980
Features extraction	1.534	3200	1.51	2100	1.534	3200
Data transmission	0	0	2.75	3600	1.2	720
Classifier training	6.315	4100	2.1	2000	2.1	2000
Testing	2.376	1900	1.2	1000	1.2	1000
Total	**15 sec**	**12240 J**	**12 sec**	**10720 J**	**10.8 sec**	**9960 J**

the minimal consumption of energy.

$$E_{\text{total}} = E_{\text{off}} - E_{\text{no off}} \tag{8}$$

$E_{\textbf{Total}}$ can have two states: negative or positive. In first case $E_{\textbf{Total}}<0$, means energy consumption during program execution on cloud (training process of our framework) is less than training the same model at local computer. This scenario encourages data offloading processing to cloud. In the latter case, $E_{\textbf{Total}}>0$, shows that energy consumption during program execution on mobile phone is less than executing the same program on cloud. This verifies the feasibility to perform computational tasks locally (that is, on mobile device).

E. ENERGY AND COMPUTATIONAL COMPLEXITY ANALYSIS

In this section, we analyze computational time and energy consumption of the proposed method to highlight its computation- and communication-saving feature. For this purpose, we incorporated the experimental practices of [37] and [38]. According to framework presented in [39], if the size of data transmission packet is 8 × 8, then energy required for its transmission is 88.48 μJ. In RGB image, each pixel consists of 24 bits (3 bytes). In gray scale image, each pixel consists of 8 bits (1 byte) while in binary image, each pixel consists of 1 bit. In the proposed framework, image size is adjusted to 256 × 256 pixels and offloaded in patches of size 8 × 8 to cloud server for further processing. Table 6 shows the approximate energy consumption both for smartphone and cloud server of mobile-cloud-based leucocytes segmentation and classification for three different computational scenarios. The full-offloading (transmission of complete blood smear image) approach consumes more energy than local and learning based adaptive-offloading (offloading image feature) approaches because of the high communication cost. Local processing approach minimizes the transmission cost, performing computationally complex operations i.e., pre-processing, segmentation, and classification at local device. However, the execution of such energy starving tasks on smartphone is not a practical approach. For such types of computationally heavy tasks, cloud servers provide a superior environment over smartphones, which is evident from the computation costs listed in Table 6.

F. PERFORMANCE ANALYSIS OF THE PROPOSED FRAMEWORK

In this section, several experiments were conducted to evaluate the performance of the proposed classification with other state-of-the-art schemes. The comparison is based on four metrics including accuracy, sensitivity, specificity, and precision as given below:

$$Accuracy = \frac{(TP + TN)}{TP + TN + FP + FN} \tag{9}$$

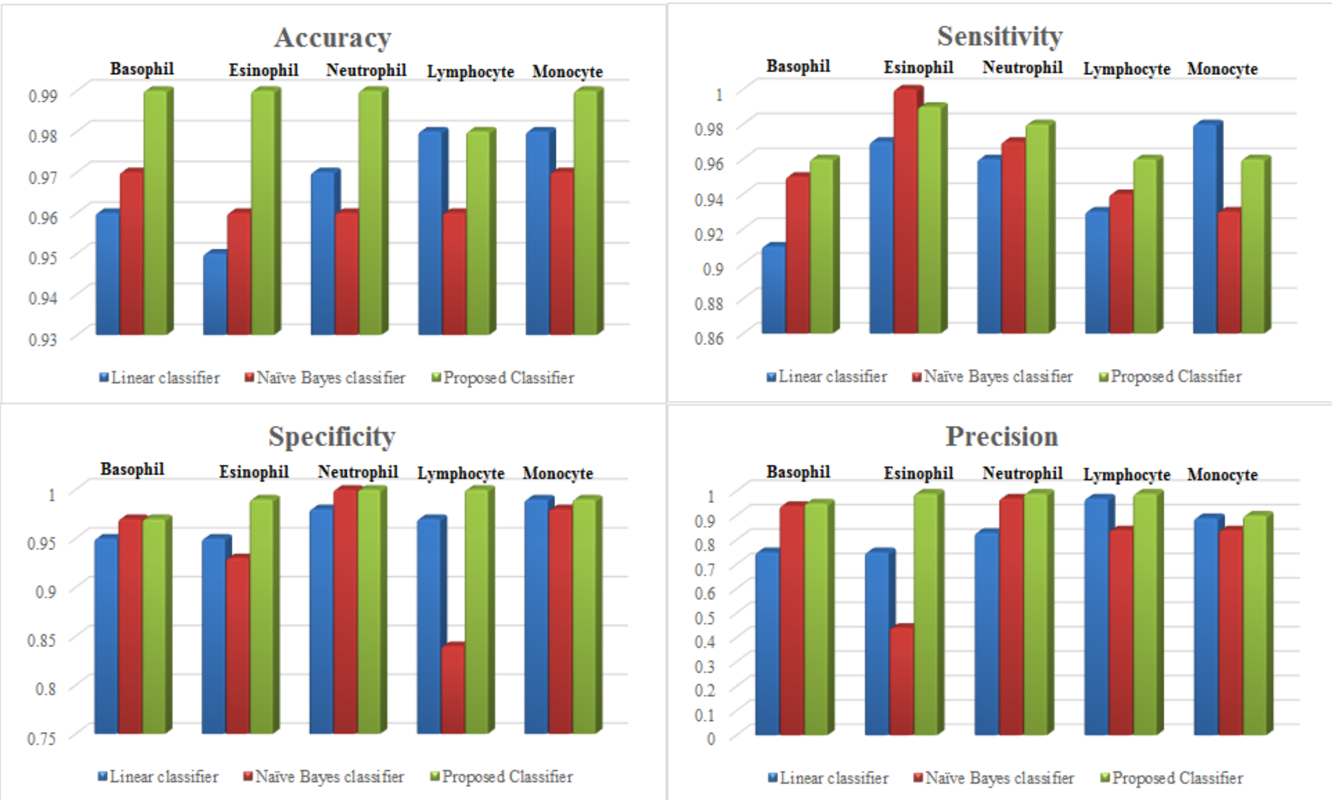

FIGURE 7. Comparative analysis of the proposed method based on accuracy, specificity, sensitivity, and precision for leukocytes classification with linear classifier.

$$Sensitivity = \frac{TP}{TP + FN} \tag{10}$$

$$Specificity = \frac{TN}{TP + FN} \tag{11}$$

$$Precision = \frac{TN}{TP + FN} \tag{12}$$

The results based on the given four metrics are shown in Fig. 7. During training, 70% of the images from the dataset were used and remaining 30% were incorporated for testing purpose. In testing phase, 98.6% average accuracy is achieved, which is far better than accuracy achieved by Naïve Bayes and linear classifier. The individual sensitivities of each leukocyte subclasses, especially subgroups like basophils, eosinophils, and monocytes, are found to be far better in the proposed framework than other state-of-the-art methods. Similarly, specificity and precision scores are higher in case of the proposed method, verifying the performance of our work compared to other methods under consideration.

VI. CONCLUSION

In this paper, a mobile-cloud assisted framework is presented for segmentation and classification of leukocytes into their corresponding five different classes. Firstly, color k-means algorithm is used to segment WBCs from blood smear images. Next, morphological operations are performed to segment the regions of interests for removing unwanted components. Then, a set of texture, geometrical, and statistical features are extracted from the segmented region. Due to the diverse nature of blood smear images, a single classifier is almost impractical. Therefore, we considered an EMC-SVM for classification of leukocytes. Experimental results confirmed that the proposed method successfully segments WBCs from blood smear images and accurately classifies each of segmented cell into their respective categories which include neutrophil, eosinophil, basophil, lymphocyte, and monocyte. The accuracy of the proposed classifier was found to be higher when compared to linear and naïve Bayes classifiers. The qualitative and quantitative results are encouraging and show that the mobile-cloud assisted framework saves energy consumption and computational time, providing accurate classification and segmentation results.

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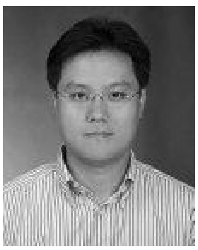

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