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Classification of Leukemia images using transfer learning approach

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ABSTRACT:Leukemia is an aggressive disease related to the white blood cells (WBC) and affects the bone marrow and blood of the human body. Acute leukemia causes fast deterioration of the patient hence an early diagnosis of the disease can be helpful in treating the disease effectively. The disease can be diagnosed by inspection of microscopic blood cell images to identify abnormalities in the cell. The state of art, covolutional neural networks are a tool of great potential in this direction. In this paper we present classification of leukemia cell (ALL)imagesusingpre trained deep learning neural network. In this paper, theperformance of CNN is measured using different parameters like accuracy, sensitivity, specificity and precision for Adaptive moment estimation (ADAM) and Stochastic gradient descent with momentum (SGDM) optimization algorithms.

Keywords: Image classification,Convolutional NeuralNetwork, Deep learning, AlexNet, ADAM,SGDM.

I. INTRODUCTION

Leukemia is a cancer of the blood cells. There are several broad categories of blood cells, including red blood cells (RBCs), white blood cells (WBCs), and platelets. Generally, leukemia refers to cancers of the WBCs. WBCs are a vital part of our immune system.The chronical disease, Leukemia can be classified into two broad categories depending on the rate of its progress as Acute and Chronic, further depending on the type of cell that it affects it isdivided into Lymphoblastic and Myeloid. Hence there are four subtypes of leukemia- acute lymphoblastic Leukemia (ALL), Acute Myeloid Leukemia (AML), Chronic Lymphoblastic Leukemia (CLL), and Chronic Myeloid Leukemia (CML) [7]. Standard promising treatments involve chemotherapy and radiotherapy.A timely and precise diagnosis of the disease can help the hematopathologist to give efficient treatment to the patient.Pathologist can identify these abnormal WBC cellsdepending on the morphological characteristics of the cells and requires a skilled medical operator. This procedure can be time-consuming, tedious, and costly [8]. Moreover, the manual analyzer may sometimes lead to the incorrect counting and classification of leukocytes [9] and can delay the treatment for the patient. Artificial Intelligence has been bridging the gap between the capabilities of humans and machines. Researchers have worked on numerous aspects of the field to make machines effectively classify images for medical applications[2]. Image processing and machine learning techniques have contributed much to the medical field[6] in diagnosing such medical images.various researchers have worked in this direction and have achieved significant results in classification of microscopic blood images usingmethods like SVM [2][3] and K-nearest neighbor [4][5] .The advancements in Computer Vision with Deep Learning have contributed to the state-of-art Convolutional Neural Network [11] in which the pre-processing required in a CNN is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, CNN have the ability to learn these filters. The role of the CNN is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction hence can take in an input image, assign importance to various aspects in the image and be able to classify one image from the other. However, in the methods of machine learning we need to design the model

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from the scratch . Also, the feature extracting and selection are time-consuming and vary according to different objects [10]. The deep neural networks (DNN), especially the convolutional neural networks (CNNs)[11], are widely used in changing image classification tasks and have achieved significant performance. In this paper we have used state of art model ie. pretrained deep convolutional neural AlexNetarchitecture [1] to classify the acute lymphoblastic(ALL) images. The paper also presents a comparison of two different optimization methodsAdaptive moment estimation (ADAM) and Stochastic gradient descent with momentum (SGDM).[11]

II. RELATED WORK

Many research works have been progressively conducted in the area of medical images.In[6]the classification of images is performed on a dataset of 260 images using computer aided diagnostic system (CAD) for detection of leukemia based on Gray level co–occurrence matrices (GLCM) and shape based features. preprocessing is performed on gray scale images to apply segmentation This approach is an effective method in classifying homogeneous stochastic textures. However, the results of this study indicate that co-occurrence matrix approach is also an effective methodin detecting the leukemic immature lymphocyte from the healthy mature lymphocyte The author has also used an Auto SVM binary classifier for better detection accuracy.

In[12] A fuzzy feature representation for white blood cell differential counting is proposed and an insight to the sensitivity of classification based on morphology of various segments of the images is signified. To diagnose types of acute leukemia(ALL)eight features categories of white blood cell are obtained based on the morphological and geometrical criteria of acute leukemiai.e., cell size, ratio of nucleus and cell size, chromatin density, nucleus shape, nucleoli, cytoplasm shape, cytoplasmic basophilic, and granule and are represented to fuzzy approach.The numerical features of each white blood cell in acute leukemia image will be extracted and then will be represented to fuzzy feature. Experiments have been conducted on a dataset of 120 images. In this a image is segmented to obtain cytoplasm and nucleus regions. The morphological values of the numerical features of each white blood cell in acute leukemia image is extracted and then represented to fuzzy features. A fuzzy decision tree is used to classify acute leukemia based on a differential countof the percentage of each fuzzy feature categories.

In [2] the approach is to isolate the whole leucocyte and then separates the nucleus and cytoplasm. This approach is necessary to analyse each cell component in detail. From each cell component,after segmenting using zackalgorithm different features, such as shape, colour and texture, are extracted after background pixel removal. This feature set was used to train different classification models in order to determine which one is most suitable for the detection of leukemia. A comparison is provided for the images with and without background

This paper [4]has proposed automatic Otsu's threshold blood cell segmentation method along with image enhancement and arithmetic for WBC segmentation extracting the shape feature of WBC images. kNN classifier has been utilized to classify blast cells from normal lymphocyte cells. The system is applied for 108 images available in public image dataset for the study of leukemia

In [13]presents a method for the automaticidentification and classification of leucocytes using microscopicimages results indicate that the proposed method isable to efficiently identify the WBCs present in an image and toproperly classifyleucoblastsClassification algorithms such as Naive Bayes, linear discriminant analysis, K-nearest neighbor, support vector machine, decision tree and ensemble random under sampling(RUS) boost are applied on leukemia dataset.Jaya is the algorithm used to improve classification accuracy.Segmentationand feature extractionis performed to extract features such aselongation, eccentricity, rectangularity, compactness, convexity, roundness. classification is performed based on SVM with various kernels ie. linear, quadratic, polynomial and Gaussian radial basis. Foreach kernel function, the parameters were tuned using optimization techniques in order to find the maximum accuracy.Author has experimented on a dataset of 300 images GUI for ALL image segmentation using BSA-based clustering has been developedJaya algorithm improves classification accuracy when applied with the existing classification algorithms.

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III. METHODOLOGY

The purpose of this investigation is to enhance the exactness of ALL image identification by using D

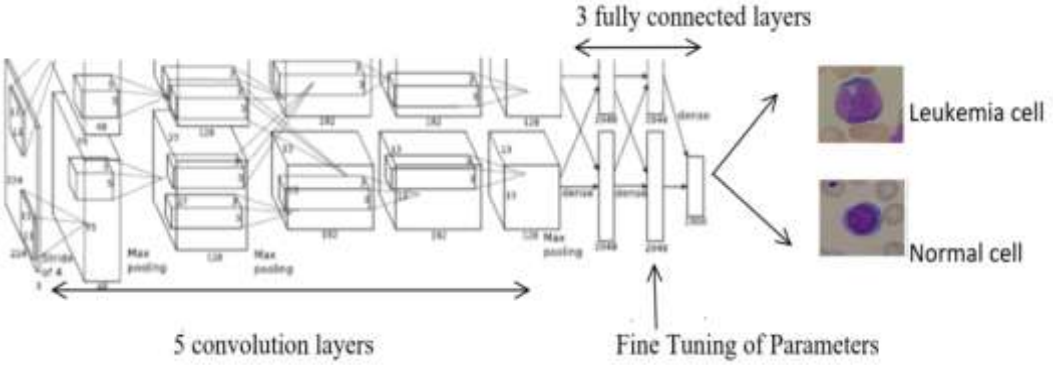

Figure 1. Alexnet architecture [1]

algorithms and Transfer Learning (TL) approach. TL is the assignment of utilizing the informationgiven by a pretrained system to learn new models provided by newdata. Calibrating a pretrained system with TL is usually a lot quickerand simpler than starting from basic. Utilizing pretrained DL systemsempowers us to rapidly learn new jobs. We here investigate the performance of AlextNetonthe given dataset. Such pretrained CNN models are utilized to performTL to extricate features that are visually distinguishable and essential.Finally, the classification of these features is done utilizing the softmaxlayer.

Transfer Learning: Transfer learning—the transfer of knowledge between tasks—is often beneficial when a limitedamount of annotated data is available, such as in image cytometry, where manual annotations are time-consuming to acquire and require a high level of expertise to make. Furthermore, CNNs trained on biomedical images, captured under specific experimental condition and imaging setups, can have poor generalizability. To overcome these limitations, large annotated datasets, like ImageNet, can be used to pretrain state-of-the-art CNNs (such as the AlexNet and GoogleNet architectures).The transferred parameter valuesproviding good initialvalues for gradient descentcan be fine-tuned to fit the target data, as we have done in this paper. This isone of the most broadly used strategies for performing TL utilizing DL systems. The extraction of visually distinguishable features is done by utilizing finetuning for every pretrained network (PTN). Fine-tuning of TL is utilized to build the proficiency and effectiveness of a Convolutional Neural Network by supplanting the last layers of the

network. In this situation, the weights of CNN are instated from the top of the PTN as opposed to supplanting and retraining the entire architecture of the classifier. This situation works by moving the weights of the PTN from source to objective dataset. The basic operation is to replace the softmax layer of the PTN and supplant it with a new softmax layer that is significant to the proposed task. In this paper, utilizing the AlexNet CNN architecture, the neurons in the objective dataset are put in place of the last fully connected layer.

Optimization techniques: The majority of DL algorithms make use of some kind of optimization techniques for either maximizing or minimizing a function $f(x)$ by varying x. This function is termed as an objective function. However, once the function is minimized it is called the cost function or loss(error) function. Gradient descent is atechnique to optimize an objective function (θ) categorized by a model's constraint $\theta \in$ Rd by revising it in the reverse direction of the objective function $\nabla_\theta J(\theta)$ w.r.t. to the parameters. 'η' which is the learning rate gives the step size taken to achieve the (local) minimum. SGDM is a technique that accelerates the descent in an appropriate path and reduces its oscillations. This is done by adding γ of the previous step update vector to the present update vector.

$$v_t = \gamma v_{t-1} + \eta \nabla_\theta(\theta)$$
$$\theta = \theta - v_t \quad (1)$$

Adaptive Moment Learning Rate (ADAM)

The adaptive moment learning rate is a form of stochastic gradient descent with an

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adaptive learning rate. Stochastic is one of the most common optimization algorithms designed to tackle the very complex problem of optimization and is commonly used in deep learning to update weights based on a subset of training samples as shown in the equation below.

$$Lt(W) = \frac{1}{b}\sum_{j=1}^{b} l\,(W; xij; yij) + \gamma r(W)$$

where $\{(xij; yij)bj = 1\}$ is the random mini-batch size chosen at iteration t, γ is the forgetting factor, L is the loss function, b the number of training samples, W are the weights, and r is the convex regularize.

The illustration for updating the weights in the Adam algorithm is shown in Table 1 [17][18]

Table 1. Steps of the Adam algorithm.

Step #	Equation	Explanation
1	$Mo = 0,\ Ro = 0$	Initialization for $t = 1, \ldots, T$
2	$Mt = \beta 1Mt - 1 + (1 - \beta 1)\nabla lt(Wt - 1)$	1st momentum estimate
3	$Rt = \beta 2Rt - 1 + (1 - \beta 2)\nabla lt(Wt - 1)^2$	2nd momentum estimate
4	$\widehat{Mt} = \frac{Mt}{(1-\beta 1)^t}$	1st momentum bias correction
5	$\widehat{Rt} = \frac{MRt}{(1-\beta 2)^t}$	2nd momentum bias correction
6	$Wt = Wt\text{-}1 - \alpha\frac{\widehat{Mt}}{\sqrt{\widehat{Rt}+\varepsilon}}$	Update
7	Return W	Returning value

where M is the 1st momentum estimate, R is the 2nd momentum estimate, $\widehat{M}$ is the 1st momentum correction, $\widehat{R}$ is the 2nd momentum correction, W is the weights, α is the learning rate, β1 and β2 are the hyperparameters, and ∇lt is the gradient evaluated at timestep t.

Metrics for assessment: The viability of the ALL detection and identification framework is assessed by calculating accuracy. It is utilized to check the effectiveness of the classifier.

(i)Accuracy: It is the ability of a system to determine the type of ALL correctly and is given by:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

(ii) Specificity: It is the ability of a system to precisely identify the genuine ALL and is calculated as:

$$\text{Specificity} = \frac{TN}{TN + FP}$$

(iii)Sensitivity: It takes into account the capacity of a model to correctly classify the ALL and is measured as:

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

(iv) Precision: It is defined as the proximity of the two measured values to each other and is given by

$$\text{Precision} = \frac{TP}{TP + FP}$$

DATABASE: In this paper, the database for detecting the leukemia cell is ALL IDB2. These images are taken from kaggle. Acute lymphoblastic leukemia-IDB 2 data set consists of 260 images having single cell where 130 images were from patients affected by leukemia and 130 were normal images. These images had resolution of 257 × 257 with 24bit color depth. In Figure.2, we can see samples of cancerous healthy images of ALL-IDB2.

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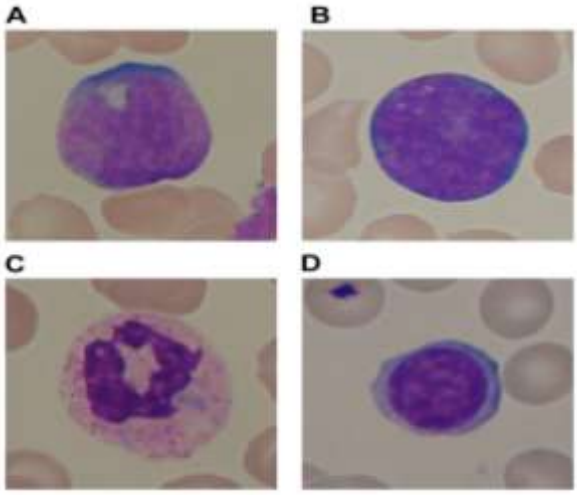

Figure 2. Acute lymphoblastic leukemiasample images.
(A) Leukemia cell, (B) leukemia cell, (C) normal cell, (D) normal cell

these images are applied to AlexNetwhich is trained using transfer learning approach to classify two classes i.eLeukemia cell or Healthy cell using transfer learning. The accuracies are compared with two different optimization techniques SGDM and ADAM. The network is trained for 20 iterations using MATLAB. The dataset is divided into 80% for training and 20% for testing. It is observed from the results that SGDM gave training accuracy of 95% and ADAM gave training accuracy of 98%.The training and error curves are shown in Figure.3 and Figure.4.
The different parameters for test dataset of ALL IDB2 are shown in table2.

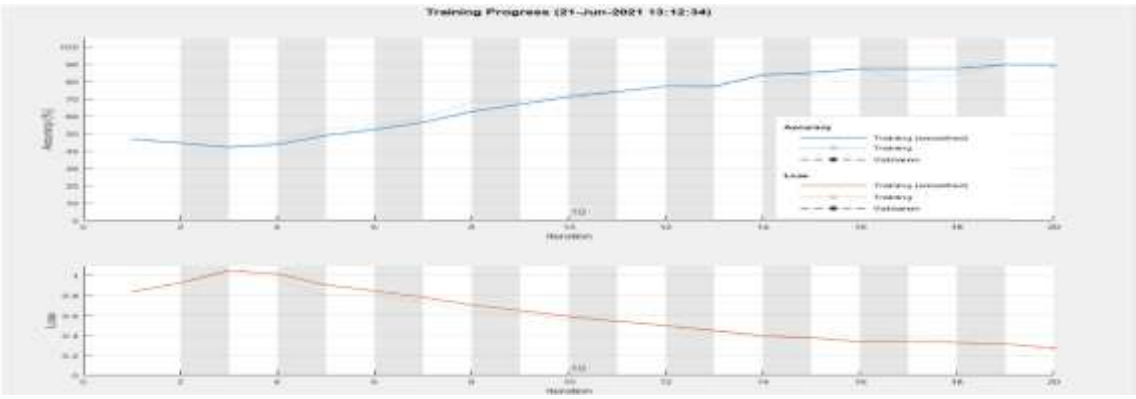

Figure 3. Training accuracy curve for SGDM optimizer

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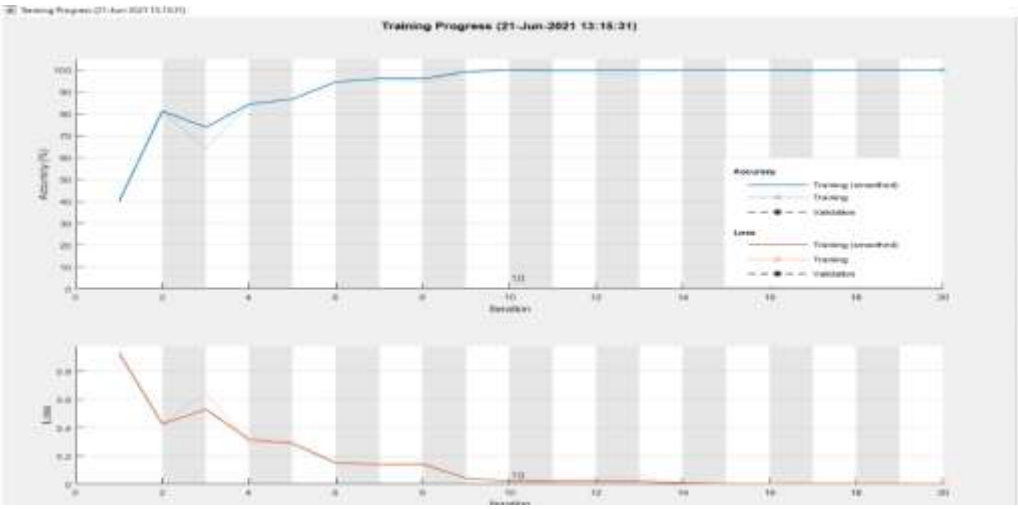

Figure 4 Training accuracy for ADAM optimizer

Table2:comparison of SGDM and ADAM optimizer for various parameters

Parameter / Optimizer	Accuracy	Specificity	Sensitivity	Precision
SGDM	0.8076	0.6923	0.9230	0.75
ADAM	.8846	.8076	0.9615	0.8333

The test accuracies are 80% and 88% for SGDM and ADAM optimization techniques respectively. It shows the if AlexNet is trained using transfer learning approach with ADAM optimization algorithm gives better results when compared to SGDM algorithm.

Conclusion: In this work, we investigated an application of DCNNs in which we deployed pretrained AlexNet for the detection and classification of ALL images. With ALL IDB2 dataset, we are able to achieve 80.7% accuracy for leukaemia detection and 88.46% accuracy for SGDM and ADAM optimization techniques respectively. This automated diagnosing system can help in early diagnosing of leukemia so that it can be treated effectively. Accuracies can be improved with data augmentation techniques and with different neural network architectures. Also, we can deploy deep learning models to learn from scratch with larger image data sets so that this diagnostic system can be used in everyday life and help the pathologist and oncologist to diagnose the leukemia in better way. Also, another future direction for researchers is todevelop an automated detection system for ALL on FPGA so that all different types of blood cancer can be automated.

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