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COMPUTATIONAL DIAGNOSIS OF BLOOD LEUKEMIA VIA IMAGE ENHANCEMENT FEATURE SELECTION BY DEEP LEARNING MODELS

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ABSTRACT

This study introduces a machine learning-based framework for classifying blood cancer (leukemia), addressing the limitations of manual diagnosis, which is often error-prone and labor-intensive. Among various machine learning methods, deep learning stands out for its ability to handle large-scale, heterogeneous medical datasets effectively. The proposed approach utilizes a feature extraction and training pipeline built on the RESNET-50 architecture, a deep neural network known for its skip connections that mitigate issues like overfitting and vanishing gradients. The system's performance was assessed using error metrics and classification accuracy, achieving an impressive 97.9% accuracy rate — a notable improvement over previous benchmarks on the same dataset, which reported 91.84%. To further enhance model reliability, extensive pre-processing techniques were applied to normalize and refine input data. The architecture's depth and residual learning capabilities enable it to capture intricate patterns in leukemic cell morphology. Comparative analysis with other deep learning models confirms RESNET-50's superior generalization performance. This advancement holds promise for integrating AI-driven diagnostics into routine clinical workflows, potentially accelerating early detection and treatment planning.

Keywords: Blood Cancer Detection, Deep Learning, Convolutional Neural Networks, ResNet-50, Classification Accuracy.

1. INTRODUCTION

TO ARTIFICIAL NEURAL NETWORKS

Artificial Neural Network (ANN) has recently emerged as one of the most powerful tools for contemporary computation. Its design is based on the fact that the human brain is a:

1) Highly Non Linear Structure

2) Highly Parallel Structure

On extremely important attribute of the neural model is its ability in following trends in the input fed to it. No matter how complex or abruptly the output for a corresponding input may change, the network maps the input and output in the form of experiences called weights. The parallel structure enables data or inputs X from various paths design the weights W. The design of the network culminates in the decision making according to some function θ called the bias. The structure can be mathematically modelled as:

$$\mathbf{Y} = \sum_{i=1}^{n} \mathbf{XiWi} + \theta$$

Here X represents the signal

W represents the weight

Ɵ represents the bias.

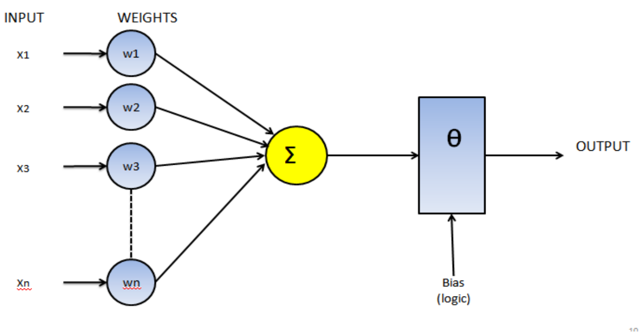

Fig 1: Mathematical Formulation of Neural Network

The referenced illustration serves as a broad conceptual representation. Accurately capturing patterns within input data is achievable through the strategic deployment of specific neural network architectures. These networks possess the inherent capability to learn and evolve dynamically in response to the input-output relationships they encounter. This adaptive behavior mirrors the cognitive processes of the human brain, which refines its responses based on accumulated experiences. In artificial neural networks (ANNs), such experiences are mathematically encoded as weights, which govern the network's learning trajectory. When a defined mapping between input variables XX and target outputs YY is provided, the network adjusts its weights to minimize discrepancies. The difference between the predicted and actual outputs is quantified as an error term EE, which can be formally expressed as:-

$$\mathbf{E = Y_a - Y_p}$$

Y_a is the actual output

Y_p is the predicted output

E is the error.

2. PROPOSED METHODOLOGY

Prior to feature extraction and classification, data pre-processing is done to achieve train the ANN accurately and obtain high sensitivity and accuracy of classification.[5]-[6]

Segmentation:

The division of an image into meaningful structures, image segmentation, is often an essential step in image analysis, object representation, visualization, and many other image processing tasks. A disjunct categorization does not seem to be possible though, because even two very different segmentation approaches may share properties that defy singular categorization1. [5] The categorization presented in this chapter is therefore rather a categorization regarding the emphasis of an approach than a strict division. The following categories are used:

Threshold based segmentation: Histogram thresholding and slicing techniques are used to segment the image. They may be applied directly to an image, but can also be combined with pre- and post-processing techniques.

Edge based segmentation: With this technique, detected edges in an image are assumed to represent object boundaries, and used to identify these objects.

Region based segmentation: Where an edge based technique may attempt to find the object boundaries and then locate the object itself by filling them in, a region based technique takes the opposite approach, by (e.g.) starting in the middle of an object and then "growing" outward until it meets the object boundaries [6]

Segmentation plays a crucial role in the feature extraction and classification. Segmentation allows to separate the region of interest from the composite image.

Considering the image under interest to have an area 'A' with a central reference 'C_0', the radial gradient is computed as:

$$\mathbf{g_r = max(r, C_0,)|G_\sigma(r)\frac{\partial}{\partial r}\oint_{r,C_0,}^{R}\frac{I(x,y)}{2\pi r}dA|}$$

Here,

g_r denotes the radial gradient

$I(x, y)$ denotes the image under interest

C_0 denotes the central reference

G_σ denotes the Gaussian kernel

r denotes the radial distance from the central reference

R denotes the maximum radial distance from the central reference

max denotes the operation to find the maxima

dA denotes the differential area

The image can be separated by computing the entropy corresponding to the grayscale histogram. The entropy of an image of m x n pixels with a histogram h_n corresponding to n grayscale levels can be expressed as [7]-[8]:

$$\mathbf{h_l = \frac{1}{1-l}log_2\sum_{i=1}^{n}p_i^l}$$

Here,

l denotes the order of entropy, and $l > 1$.

p_i^l denotes a discrete probability distribution corresponding to the histogram h

As $\lim_{l \to 1} h_l$ approaches the Shannon's entropy. The segmentation of the image into n levels would yield an additive entropy given by:

$$E_l(t) = Arg\ max\{\sum_{i=1}^{n} h_l c_i\}$$

Here,

$E_l(t)$ denotes the additive entropy

c_i denotes the number of categories of segmentation corresponding to the value of n

In case the image is contrast enhanced, the segmentation becomes more effective [8]

Classification using Deep Nets

The most common deep learning approach used for image classification happens to be the convolutional neural network (CNN). The CNN is an extremely effective deep learning based classifier which performs pattern recognition in each of its layers based on stochastic computing. The fundamental operation in the CNN hidden layers is the convolution operation mathematically given by [9]:

$$x(t) * h(t) = \int_{-\infty}^{\infty} x(\tau) h(t - \tau) d\tau$$

Here,

x(t) is the input

h(t) is the system

y is the output

*is the convolution operation in continuous domain

For a discrete or digital counterpart of the data sequence, the convolution is computed as [10]:

$$y(n) = \sum_{-\infty}^{\infty} x(k) h(n - k)$$

Here

x(n) is the input

h(n) is the system

y is the output

*is the convolution operation in discrete domain

A CNN has the following salient features:

1) Strided convolution: While conventional convolution is an overlap between the system and the data, strided convolutions help in covering all the data samples rather than just the internal samples of the data matrix. The stride over is just a hop in convolution [11]. Mathematically, for an (n x n) and (f x f) convolution, if 'p' is the number of strides, then the number of samples in the output are [12]:

$$Y_{Samples} = \left(\frac{n + 2p - f}{s} + 1\right) \left(\frac{n + 2p - f}{s} - 1\right)$$

Here,

n is the input sample matrix dimension

f is the system sample matrix dimension

p is the stride length

2) Pooling and Max Pooling: The pooling is an operation to make the features more robust and reduce the dimensionality. Typically, max-pooling is employed [13].

3) Employing Weighted Gradient Descent: The gradient descent is used as the most common and effective cost function optimization based CNN training algorithm. It is given by [14]:

$$w_{k+1} = w_k - \alpha \frac{\partial e}{\partial w}$$

Here,

w_{k+1} is the weight of the next iteration

w_k is the weight of the present iteration

e is the error

α is the learning rate

The typical structure of a CNN is depicted in figure 2.

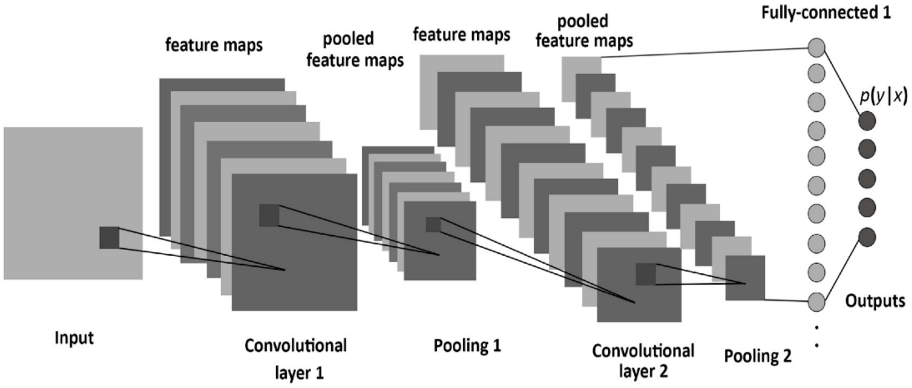

Fig 2: Typical CNN Structure [15]

An additional classifier integrated into this study is the Residual Network (ResNet), an advanced variant of the widely adopted Convolutional Neural Network (CNN) architecture. ResNet enhances traditional CNNs by introducing residual connections, which facilitate deeper network training and mitigate issues such as vanishing gradients. [16]. ResNet consists of multiple convolutional layers, but unlike standard CNNs, it incorporates skip connections between layers. These residual links prevent the direct flow of weights through hidden layers, helping to reduce vanishing gradients and improve learning efficiency.

1) Reduces the chances of overfitting the network.
2) Avoiding the chances of vanishing gradient commonly encountered in conventional CNNs.

The network architecture comprises 48 convolutional layers and a single Max-Pooling layer. It employs the ReLU activation function with a stride of 2 for efficient feature extraction and non-linear transformation. [17]. Increasing the depth of conventional CNNs often results in performance saturation, limiting their ability to learn effectively. ResNet overcomes this challenge through the use of skip connections and identity mappings, which facilitate smoother gradient flow and enable deeper network training without degradation. [18].

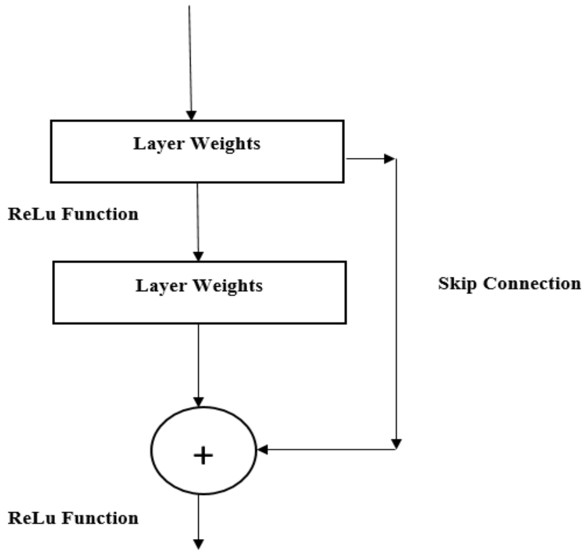

Fig 3: The ResNet Architetcure

The performance of the two training algorithms are evaluated subsequently in terms of classification accuracy. The concept of skip connections in the ResNet is depicted in figure 3 [19].

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The ResNet architecture used in the proposed work has an input size of 243x243x3 for the separate R,G and B channels of the image. A max pooling of 2x2 with a stride of 2 has been used. The feature layer of $Fc1000$ was employed with 1000 feature vectors.

3. EVALUATION PARAMETERS

The various parameters for the classification are [20]:

1. **True Positive (TP):** It is the case when a sample belongs to category and the test also predicts its belongingness.
2. **True Negative (TN):** It is the case when a sample does not belong to category and the test also predicts its non-belongingness.
3. **False Positive (FP):** It is the case when a sample does not belong to category and the test predicts its belongingness.
4. **False Negative (FN):** It is the case when a sample belongs to category and the test predicts its non-belongingness.

Accuracy (Ac): It is mathematically defined as:

$$\frac{TP + TN}{TP + TN + FP + FN}$$

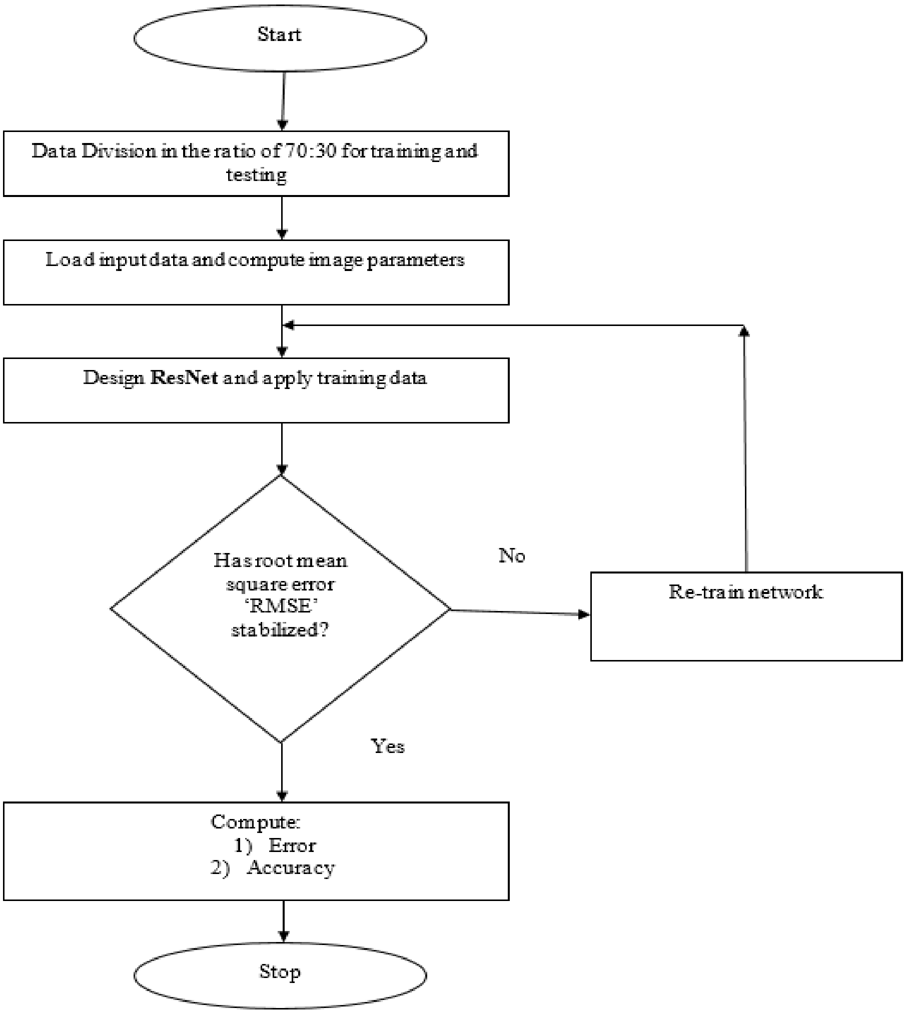

Fig 4: Proposed Flow Chart

4. RESULTS

The results have been simulated on MATLAB 2020a. The data has been collected from: ALL-DB

Acute Lymphoblastic Leukemia Image Database for Image Processing

http://www.dti.unimi.it/fscotti/all

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Fig 5: Original Image

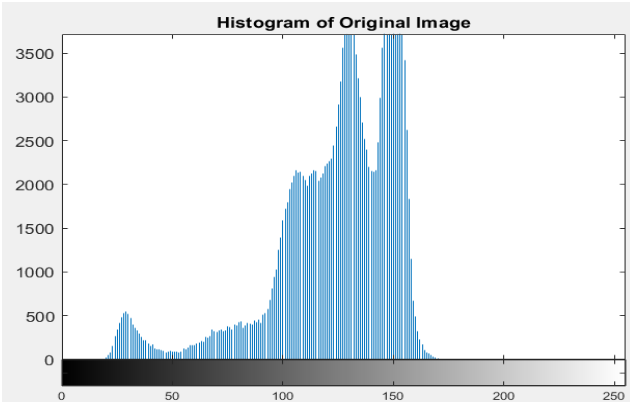

Fig 6: Histogram of Original Image

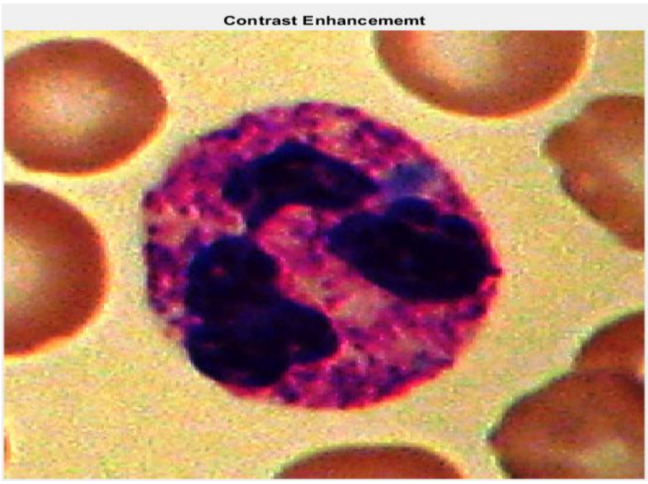

Fig 7: Contrast Enhanced Image

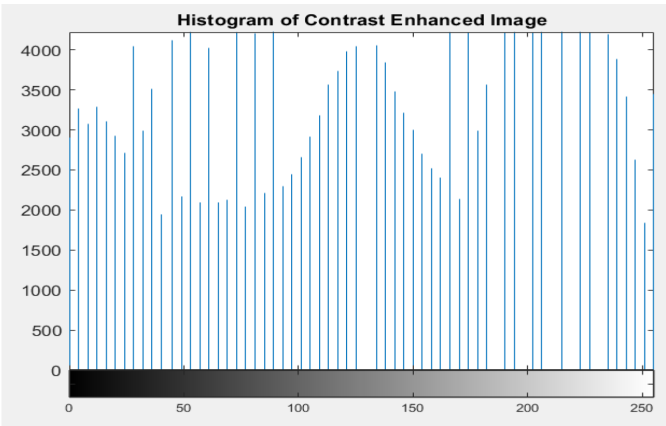

Fig 8: Histogram of Contrast Enhanced Image

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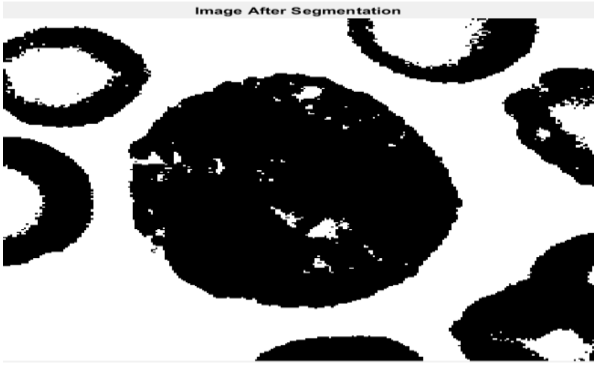
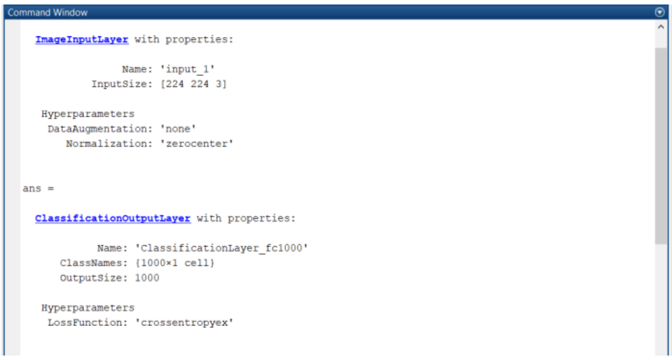


Fig 9: Image after Segmentation with radial gradient and Shannon Entropy




```
ImageInputLayer with properties:

          Name: 'input_1'
     InputSize: [224 224 3]

  Hyperparameters
    DataAugmentation: 'none'
       Normalization: 'zerocenter'


ans =

  ClassificationOutputLayer with properties:

          Name: 'ClassificationLayer_fc1000'
    ClassNames: {1000×1 cell}
    OutputSize: 1000

  Hyperparameters
    LossFunction: 'crossentropyex'
```

Fig 10: ResNet Properties

```
Hyperparameters
  LossFunction: 'crossentropyex'
```

The default loss function for classification is cross entropy for k mutually exclusive classes.

Include a classification output layer in a Layer array.

```
layers = [ ...
    imageInputLayer([28 28 1])
    convolution2dLayer(5,20)
    reluLayer
    maxPooling2dLayer(2,'Stride',2)
    fullyConnectedLayer(10)
    softmaxLayer
    classificationLayer]

layers =
  7x1 Layer array with layers:

     1   ''   Image Input             28x28x1 images with 'zerocenter' normalization
     2   ''   Convolution             20 5x5 convolutions with stride [1  1] and padding [0  0  0  0]
     3   ''   ReLU                    ReLU
     4   ''   Max Pooling             2x2 max pooling with stride [2  2] and padding [0  0  0  0]
     5   ''   Fully Connected         10 fully connected layer
     6   ''   Softmax                 softmax
     7   ''   Classification Output   crossentropyex
```

Fig 11: Layer Properties

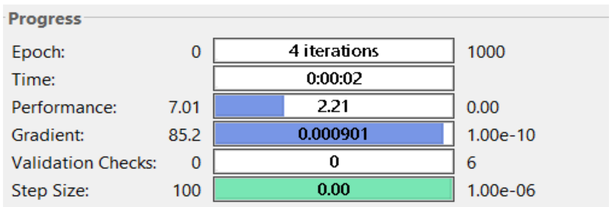


Fig 12: Training Parameters

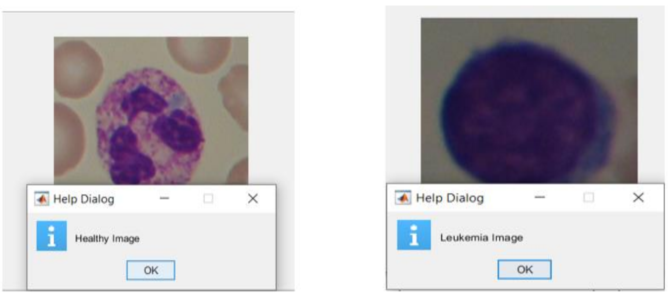


Fig 13: Classification as Healthy and Leukemia

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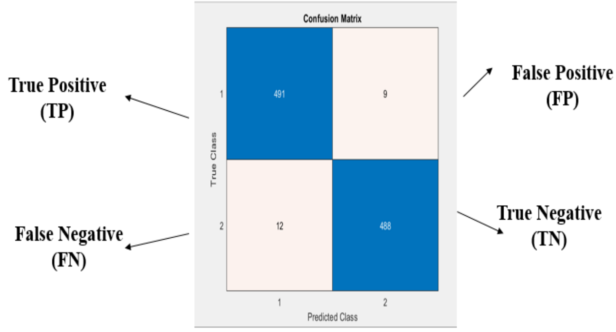

Fig 14: Confusion Matrix

$$Ac = \frac{TP + TN}{TP + TN + FP + FN} = \frac{\text{Correct Decisions}}{\text{Total Decisions}}$$

$$Ac = \frac{491 + 488}{491 + 488 + 9 + 12} = \frac{979}{1000} = 97.9\%$$

Table 1: Summary of Results

S.No.	Parameter	Value
1.	Dataset	ALL-DB Acute Lymphoblastic Leukemia Image Database for Image Processing http://www.dti.unimi.it/fscotti/all
2.	Architecture	RESNET-50
3.	Training	Gradient Descent
4.	Iterations	4
5.	Classification Error	2.1%
6.	Accuracy	97.9%
7.	Accuracy of Previous Work [1]	91.84%

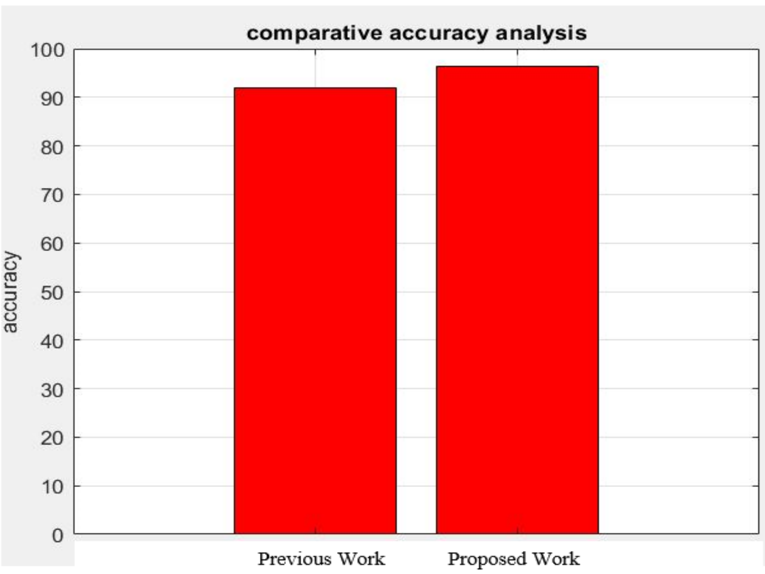

Fig 15: Compared Accuracy Analysis

5. CONCLUSION

It can be concluded form the previous discussions that the proposed system achieves high values of accuracy in the detection and classification of Microscopic Blood images. This work will act as supportive tool for radiologists and will help doctor for fast and reliable diagnosis based on which the course of treatment plan can be decided. The proposed work uses segmentation and ResNet 50 convolutional neural network for classification The ResNet 50 avoids the chances of overfitting and vanishing gradient. The training approach used is the gradient descent with the objective function being root mean square error. The system trains in 4 iterations. The accuracy achieved by the proposed technique is 97.9% which is significantly higher than the existing approach. Thus the proposed technique can be used as an effective tool for blood cancer detection.

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