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Leukemia Blood Cancer Detection

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ABSTRACT

Automatically generated identification of cancers of the leukocytes, which include Leukemia, is a tricky biomedical research problem. Many sorts of laboratory procedures that take hours are used to manually detect leukemia. In this paper, we have suggested a method for detecting leukemia that is both quick and accurate. The proposed methodology intends to detect leukocyte cancer early, reduce cases of false positives, and improve the learning methodology of the system. Here we have implemented 3 different pre- trained deep learning models namely Inceptionv3, Xception and Resnet50 for identifying the cancer cells presence. And all the 3 models performed well with the accuracy of 80%, 92.88 % and 98.15% respectively.

Keywords - Image Classification, White Blood Cells, Leukocytes, Deep Learning,

I. INTRODUCTION

Leukemia is the most serious type of blood cancer, which affects both children and adults. The majority of cancer cells start in bodily parts, but leukemia is a type of cancer that starts in blood cells and thrives there. Cells proliferate and multiply into new cells in the human system. In order for new cells to take their place, old cells are eliminated. In cancer, old cells do not die and linger in the bloodstream, leaving young cells with little space to live. As a result, blood function is disrupted, and white blood cell production is aberrant and uncontrolled.

On a daily basis, billions of these cells, predominantly RBCs, are created. These cells do have a life cycle and perish at regular intervals. Blood is composed of platelets, red blood cells (RBC), and white blood cells (WBC).Platelets help with clotting and preventing bleeding. The red blood cells, or erythrocytes, are in charge of carrying oxygen from the lungs to the body's tissues. White blood cells (WBCs), also known as leukocytes, fight infections and diseases. The creation of a large number of premature WBC is referred to as leukemia.

Bone marrow produces an abnormal number of WBCs in leukemia as compared to the other two types (RBCs and platelets). Such premature cells, commonly called blasts, are unable to perform their normal functions and crowd out other cells, causing their function to be compromised. White blood cells (WBC) are further divided into two groups. Lymphoid and myeloid cells are two types of cells.

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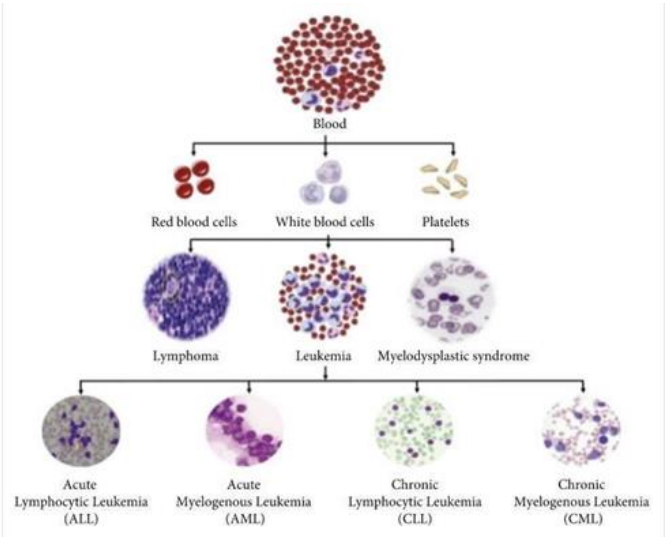

Fig 1. Blood cancer family tree

Leukemia is broadly categorized as lymphoblastic leukemia or myelogenous leukemia depending on which of these types of white blood cells has multiplied. On the basis of how quickly the disease advances, it can be classified as acute or chronic leukemia. Because blast cells proliferate at a fast rate in acute leukemia, the disease deteriorates quickly, whereas blast cells grow slowly in chronic leukemia. The four types of leukemia that can be diagnosed using both criteria are:

1) Acute Lymphoblastic Leukemia (ALL)
2) Acute Myelogenous Leukemia (AML)
3) Chronic Lymphoblastic Leukemia (CLL)
4) Chronic Myelogenous Leukemia (CML)

II. SYSTEM ARCHITECTURE

The developed approach for identifying blood cancer in human blood samples utilizing microscopic blood cell images is shown in Fig 2. Image data augmentation is a process that involves producing changed versions of the images in a training dataset to artificially expand it. As the dataset already contains separate folders for train, test and validation .We just have given the required path for deep learning pre-trained models. After loading the base model we only need to compile it and fit it.

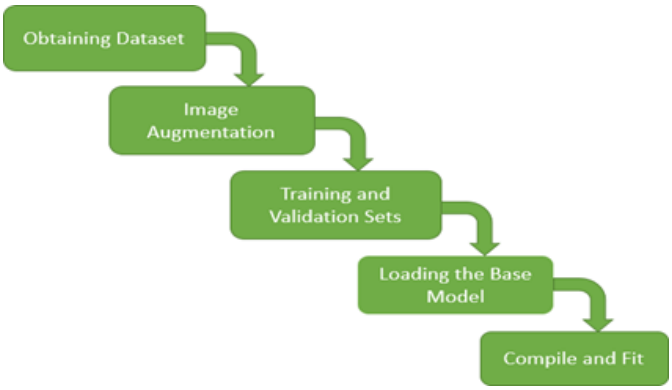

Fig 2 .System Architecture

III. DATASET

Experiments are carried out on a dataset that has been downloaded from [8].

The dataset is divided into 3 classes train, test and validation. And each folder further contains two more folders namely Cancer and Normal.

Dataset Info	Total Images	Cancer Images	Normal Images
Training Dataset	4961	2478	2483
Testing Dataset	1240	620	620
Validation Dataset	10	4	6

Table 1.Dataset Description

IV. TECHNICAL WORK

4.1. ResNet 50 Model:

A convolutional neural network with 50 layers is known as ResNet-50. The ImageNet database contains a pre-trained version of the network that has been trained on over a million photos. The network can identify photos into 1000 different object categories, including keyboard, mouse, pencil, and a variety of animals. As a result, the network has picked up rich feature representations for a variety of images. The network accepts 224-by-224-pixel images as input.

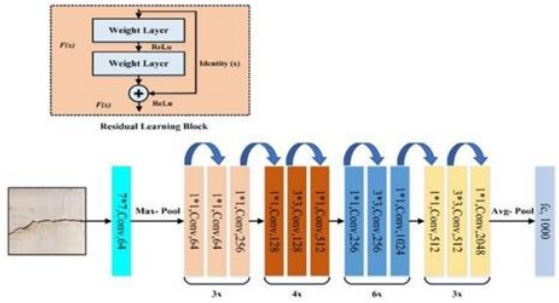

Fig 3 .ResNet 50 Architecture

4.2. Xception Model:

Xception is a Depth Wise Separable Convolutions-based deep convolutional neural network architecture. The "extreme" version of an Inception module is known as Xception. Xception stands for "Extreme Inception" and draws the concept of Inception to a logical conclusion. Inception compressed the original input by a 1x1 convolution, and each of these input spaces had a different filter type for each depth space. Xception simply reverses this process. Rather, it applies the filters to each depth map sequentially before compressing the input data using 1X1 convolution across the depth.

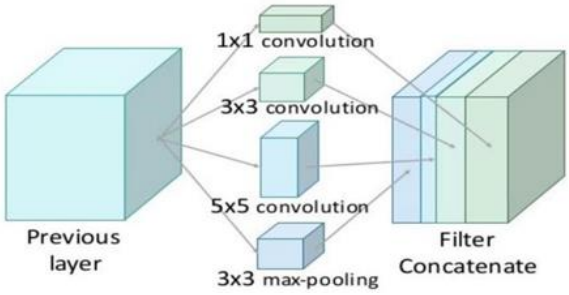

Fig 4. Xception model architecture

4.3. InceptionV3 Model:

Convolutional neural networks (CNNs) using Inception Modules are used to cut down on processing costs. Neural networks must be designed effectively since they deal with a large number of images with a wide range of featured visual material, also known as salient sections. Convolution is performed on an input with not one, but three different sizes of filters in the most basic version of an inception module (1x1, 3x3, and 5x5). Maximum pooling is also done. The outputs are then concatenated and transmitted to the following layer. The network develops progressively wider, not deeper, by configuring the CNN to complete its convolutions on the same level.

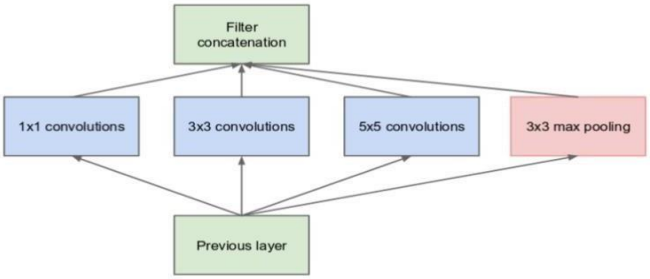

Fig 5. Inception model architecture

V. RESULT

Model	Accuracy
ResNet 50	98.15%
Xception	92.88%
InceptionV3	80%

Table2. Various deep learning models accuracy

Here we have implemented 3 different pre-trained deep learning models namely Inceptionv3, Xception and Resnet50 for identifying the cancer cells presence. And all the 3 models performed well with the accuracy of 80%, 92.88 % and 98.15% respectively.

We got the greatest accuracy of 98.15% for the ResNet50 and it was used in our existing system.

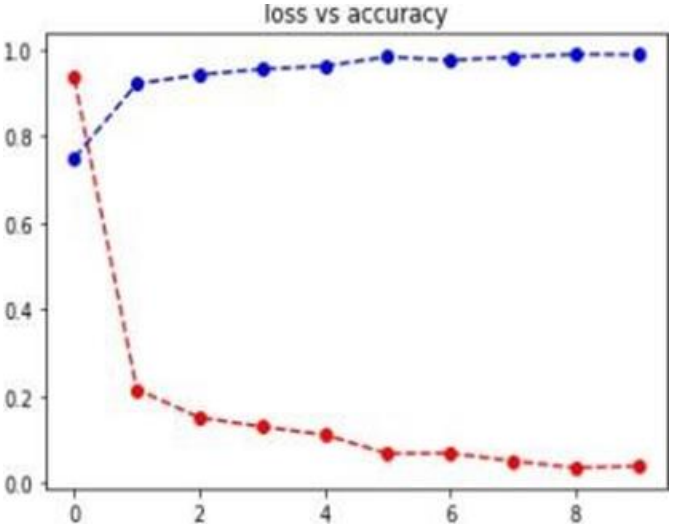

Fig 6. ResNet Model Loss VS Accuracy

Fig 7. Detection of cancer blood cell

Fig 8. Detection of normal blood cell

VI. CONCLUSION

We have implemented in this paper, a fully automatic system that would accurately identify Leukemia cancer. Firstly, for model creation we have taken blood microscopic images from train and testing dataset and then utilized 3 pre-trained deep- learning models for checking accuracy namely InceptionV3(80%), Xception(92.88%) and ResNet50(98.15%), out of which ResNet50 was used for further procedure for cancer prediction with help of Graphical User Interface (GUI).

High reliability, accuracy, efficiency, reduced processing time, reduced error, and robustness are all features of our system.

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