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AUTOMATIC DETECTION OF WHITE BLOOD CELL CANCER TYPE USING BONE MARROW MICROSCOPIC IMAGES

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Abstract: Leukemia is a condition that affects the bone marrow and/or blood and is related to white blood cells (WBC). The ability to diagnose leukaemia in its earliest stages quickly, safely, and accurately is crucial for both treating and preserving patients' lives. According to advances, there are two main types of leukaemia: acute and chronic. Blood cancer develops as a result of the unchecked proliferation of these white blood cells. The suggested work offers a reliable method for categorising Multiple Myeloma (MM) and Acute Lymphoblastic Leukemia (ALL) using the SN-AM dataset. The bone marrow overproduces lymphocytes in Acute Lymphoblastic Leukaemia (ALL) and Multiple Myeloma (MM) results in the accumulation of cancer cells in the bone marrow as opposed to their release into the bloodstream. The model pre-processes the images and then extracts the best features after being trained on cell images. The model is then trained using the RestNet50, and it concludes by predicting the type of cancer that is present in the cells. A Convolutional Neural Network (CNN) with 50 layers deep is called RestNet50.

Keywords: ResNet50, CNN, Acute Lymphoblastic Leukaemia, Multiple Myloma

I.INTRODUCTION

Image processing is the process of enhancing the quality of an image or extracting useful information from it[5].Digital image processing refers to the transformation of an image into a digital format[5]. Modern cameras can capture images in digital format immediately, however most photos are captured optically. They are digitalized after being captured by video cameras. Deep neural networks are used to conduct image processing tasks such as reducing picture noise and performing image-to-image translation, Deep Learning Tool box is required[5]. Deep learning use neural networks to extract valuable feature representations from data[1]. Deep learning is a machine learning and artificial intelligence (AI) technique that mimics how humans acquire knowledge[1]. Deep learning is a type of machine learning that uses data representations rather than task-specific algorithms to learn. There are three types of learning: supervised, semi-supervised, and unsupervised. Convolutional Neural Networks are one of the most promising techniques in this field (CNNs)[1].It allows us to train an AI to predict outputs, given a set of inputs. Both supervised and unsupervised learning can be used to train the AI. The iterative aspect of machine learning is important because as models are exposed to new data, they are able to independently adapt. A Convolutional Neural Network (CNN, or ConvNet) is a class of deep neural networks[1].ResNet50 is regarded as a superior deep learning architecture since it is reasonably simple to optimise and achieves higher accuracy[6].
This work proposed to design Automatic Detection of White Blood Cancer Cell Type from Bone Marrow Microscopic Images using ResNet50 Architecture. It detects which type of cancer, the white blood cell is affected with and which type of white blood cell is affected extremely.

II. METHODOLOGY

The Proposed system model, containing three types of layers, namely convolutional layer, max pooling layer and fully connected layer, is trained on the training set and then it is used for prediction on the testing set. CNN model is implemented for training the feature of white blood cancer cell. This model uses microscopic smear images from WBC's nuclei[2]. ResNet50 is a Convolutional neural network which have a large impact on the field of deep learning, specifically in the application of deep learning to machine vision.

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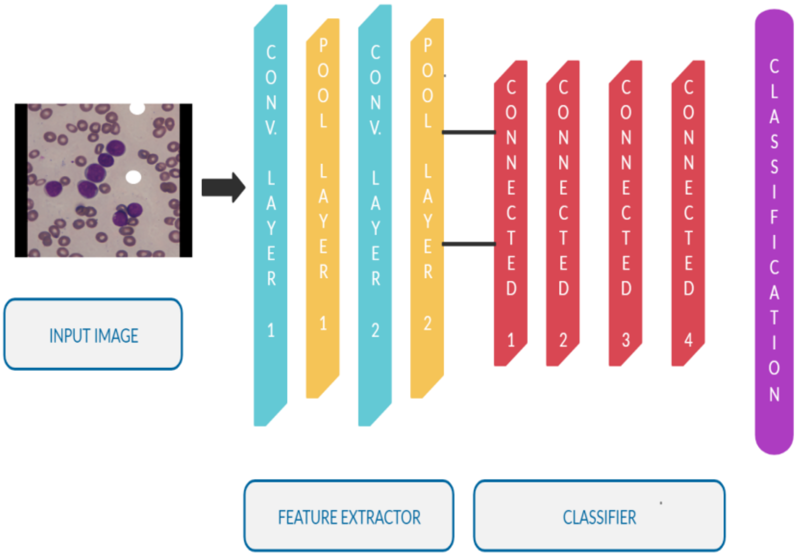

Figure 1: CNN Architecture

Convolution is a form of linear operation that is used to extract features. Convolution processes the incoming images through a series of convolutional filters, each of which activates different aspects of the images[2]. A pooling layer's main goal is to reduce the number of input parameters and hence reduce overfitting - obtain representative features from the input. It aids efficiency by reducing computation. Feed forward neural networks are what the Fully Connected Layer is all about. Fully Connected Layers are the network's final layers. The output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer, is the input to the fully connected layer[1].
A convolutional neural network with 50 layers is called ResNet-50. Since ResNet50 can achieve greater accuracy and is reasonably simple to improve, it is regarded as a superior deep learning architecture[6]. Additionally, vanishing gradient issues are a constant and are fixed by the network's skip connections. The network's time complexity rises in direct proportion to the deep network architecture's layer count[1]. The ImageNet database contains a pre-trained version of the network that has been trained on more than a million images. The pre-trained network can categorise photos into 1000 object categories. ResNet has been applied to tasks like identification, segmentation, and detection[6]. A ResNet model version called ResNet50 contains 48 Convolution layers, 1 Max Pool layer, and 1 Average Pool layer[6]. A common ResNet model is this one. With the framework ResNet's provided, it was feasible to train extremely deep neural networks while still obtaining excellent performance[1].

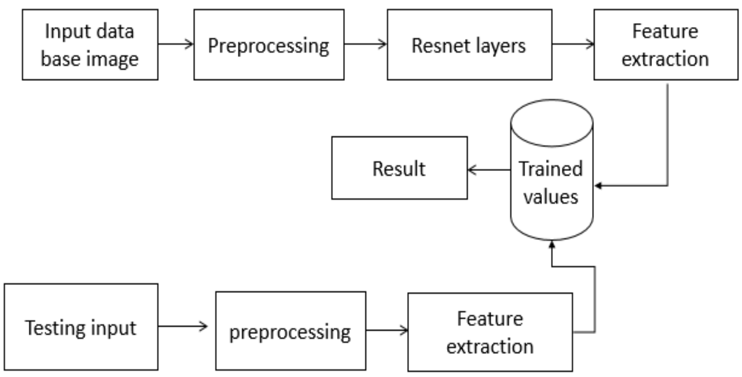

Figure 2: Block Diagram

The above diagram represents the blocks of ResNet Architecture. First, an image data to be trained is provided as an input to the system which is then preprocessed and sent to different ResNet layers[6]. After going through different layers such as convolutional layer, max pooling layer, fully connected layer etc., the features of the image are extracted

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and the model is trained. Then, the image data to be tested is given as input and is preprocessed and its features are extracted[3]. Then these features are compared with the already trained values and the result is obtained.

III.RESULT

A.Trained input

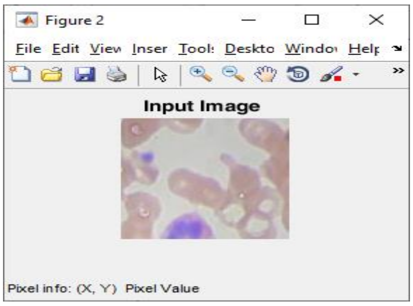

Figure 3: Cancer affected White Blood Cell

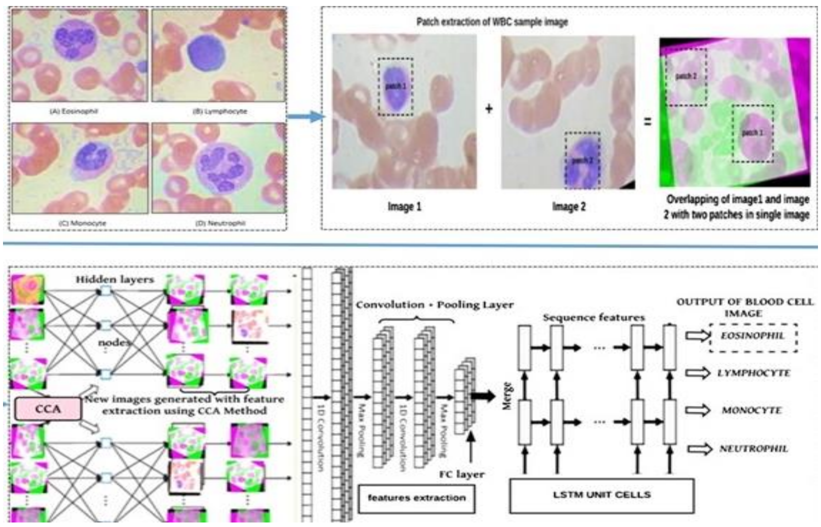

Figure 4: Training and Testing Process

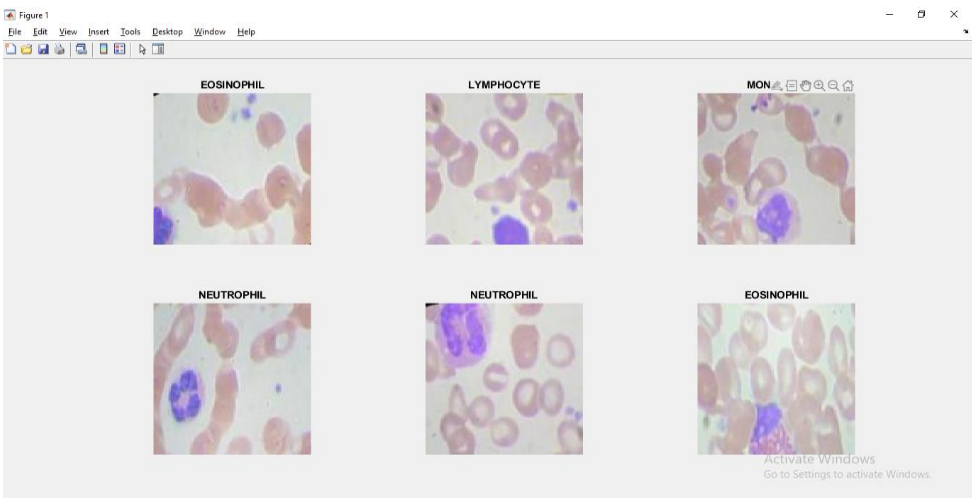

Figure 5: Trained image (WBC Types)

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Figure 3 shows the trained input image which is a cancer affected white blood cell from bone marrow microscopic smear images. Figure 4 illustrates the whole process of training and testing using ResNet50 algorithm. First, feature extraction is carried on the input image by the convolution and pooling layer. The extracted features are then processed by fully connected layer which has four types of WBC smear images (Figure 5). The output from the fully connected layer is given to soft max layer which is responsible for decision making and gives the final result.

B. Output images

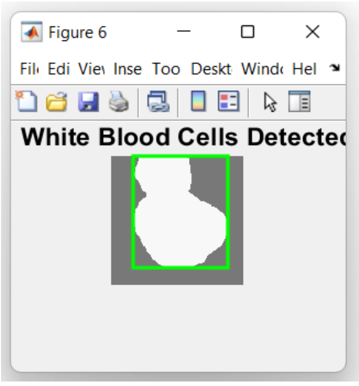

Figure 6: White blood Cell Detection

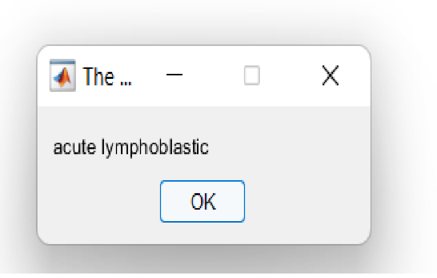

Figure 7: Detection of Cancer cell Type

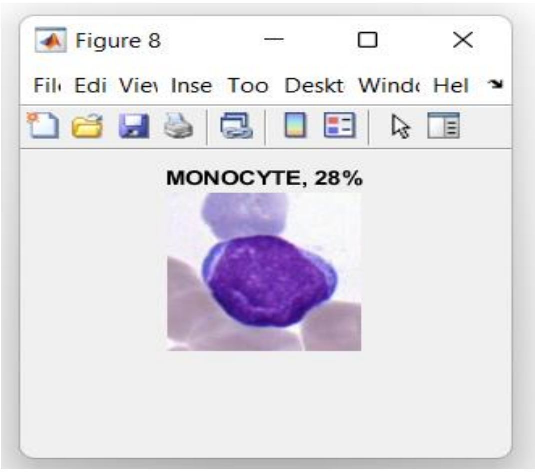

Figure 8: Cancer affected WBC's Type Detection

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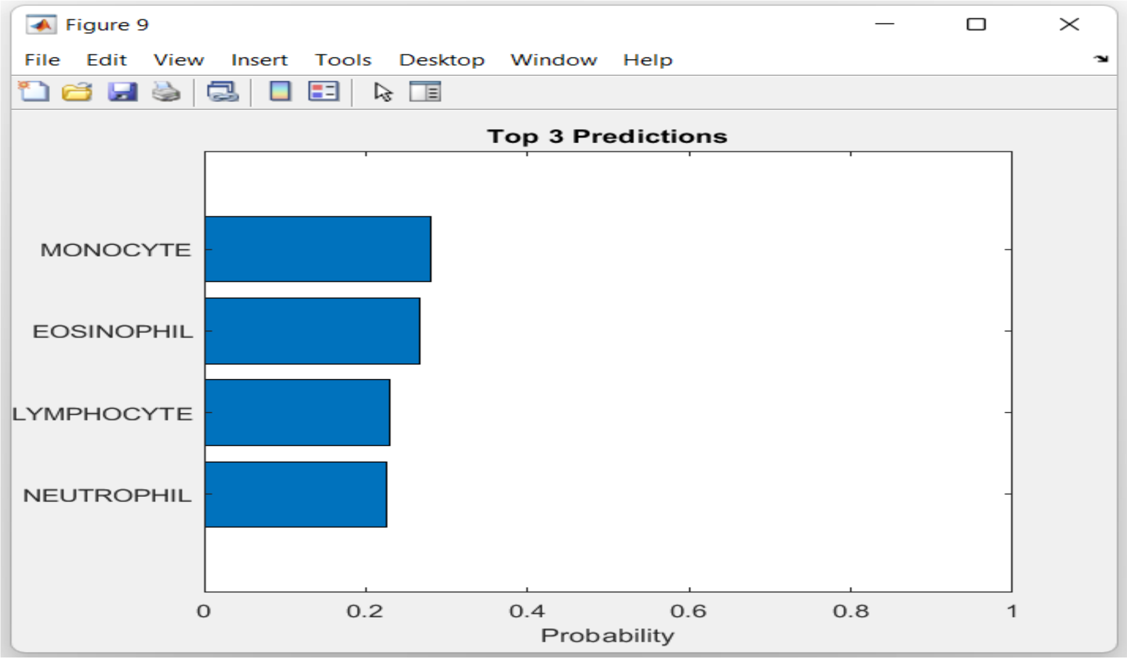

Figure 9: Prediction Graph

The figures displayed are the sequence of outputs that we obtain from this project. Figure 6 represents the detection of White Blood Cells from Bone marrow microscopic images. Figure 7 denotes the detection and analysis of cancer cell type by the process of testing. The type of white blood cell cancer that has affected the cells is detected. Figure 8 shows a seriously affected type of WBC. The Prediction graph represents the probability of the presence of cancer in different types of white blood cells. The extremely affected type of WBC is predicted in the graph (Figure 9). With the help of these results, cancer type can be detected and treatment can be proceeded with accordingly, since early detection helps in curing this disease to a much greater extent.

IV.CONCLUSION

By employing a complete learning technique, specifically convolutional neural systems, the suggested model completely eliminates the possibility of mistakes in the human process. The model first pre-forms the images and isolates their best features before being prepared with a modified Convolutional neural network structure. Finally, it makes a prediction about the cancer kind shown in the image. As a result, the model can be effectively used as a means to assess the type of malignant development in the bone marrow.

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