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Streamlined Classification of Microscopic Blood Cell Images

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Abstract: Deep learning is a kind of AI that mimics how humans learn certain things. Unlike traditional machine learning algorithms, deep learning algorithms are piled high with increasing complexity and abstraction. Image classification is a subject of Deep Learning where we may categorize photos into classes based on their attributes. White blood cells are a component of the body. They help the body fight infections and disorders. Neutrophils, lymphocytes, monocytes, and eosinophils are white blood cells. The classification algorithm may be used to classify current data based on coaching knowledge. A software learns from a dataset or collection of observations and then classifies fresh data into classes or groups. This work aims to propose a newly deviced CNN model called LYMPONET which has been employed to differentiate the types of white blood cells, which may be used to predict many autoimmune disorder. LYMPONET is a bespoke CNN-based architecture that performs better than existing CNN models like VGG16, InceptionV3, Xception, and ResNet152V2, as measured by performance measures.

Keywords: *Deep Learning, Autoimmune diseases, WBC, Convolutional Neural Network*

1. Introduction

WBC are vital to the body. Their job is to combat illness and maintain health. All white blood cells are granulocytes (neutrophils, eosinophils, and basophils) (T cells & B cells). The WBC count ranges from 4,500 to 11,000 per microliter. All autoimmune illnesses stem from a lack of white blood cells, which help defend us from germs, viruses, and parasites. Each autoimmune illness is caused by a deficit in a certain kind of white blood cell.Deep Learning can categorise WBC kinds based on picture categorization with reduced error. Deep literacy is a kind of machine learning, which mimics human knowledge acquisition. Data wisdom covers statistics and predictive modelling and requires deep knowledge.

A machine learning approach that trains computers to perform what people do instinctively. monitored, semi-supervised, or unsupervised. Convolutional neural networks do image categorization as supervised learning. With a convolutional neural network, you can compare and rank how important different parts or objects are in a picture.

2. Related Works

Li Ma et al [1] proposed combining DC-GAN and ResNet for blood cell image categorization. . Deep Convolutional Generative Adversarial Networks (DC-GAN) and Residual Neural Networks are the algorithms under discussion (ResNet). DC-GAN and ResNet are used to classify blood cell pictures in this study. The accuracy metric, which is roughly 91.68 percent, is the performance metric.

A model was released by Elsevier in 2020. A.M. Patilc and colleagues [2]. Their research employs CNN, Xception and recurrent neural networks LSTM to categorise White Blood Cells images using Deep Learning with Canonical Correlation Analysis (a combination of CNN and RNN). The accuracy rate for this categorization is 95.89 percent.

Model MGCNN [3] was produced in the IEEE (Journal on Biomedical and Health Informatics) in 2020. Using hyperspectral images and modulated CNN, we used the MGCNN (Modulated Gabor wavelet and deep convolutional neural network) approach to categorise blood cells. The accuracy performance metric for this domain is 97.65 percent.

Subclass grouping of White Blood Cell Images Mesut Togacar, et al [4]. Published Using Convolutional Neural Network in 2019. For the categorization of WBC pictures from the provided datasets, they employed the AlexNet CNN Architecture technique. The performance metric for this project is accuracy, which is given as 97.78 percent.

Convolutional neural networks [5] were recently used to recognise peripheral blood cell images, and this technique was proposed in 2019. Andrea Acevedo and colleagues, who generated and worked on this study, This technique was utilised to offer identification of blood cell images using CNN and the VGG16 algorithm. We gathered information for this excerpt from

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the journal Elsevier. The correctness of this project is measured by the rate of domain, which is roughly 96 percent.

For WBC Classification Using CNN from Springer Link in 2019, a LeNet-5 Architecture algorithm-based technique [6] was employed. Authors like Mayank Sharma and others effectively exposed this work. This paper's performance metric is accuracy, which yields a do-main rate score of about 87 percent.

In 2018, the WBC Classification and also add up Using CNN method and AlexNet convolutional neural network architecture techniques were presented at the IEEE third International Conference ICCARE [7]. Authors like Merl James Macawile and others developed this paradigm. According to the performance metric, the accuracy rate for this domain is around 96.63 percent.

Inception Recurrent Residual CNN algorithm-based Blood Cell Classification [8] using Inception and Recurrent Residual CNN was suggested in 2018. Author, Zahangir Alom and those who contributed to this work. The IEEE National Aerospace and Electronics Conference was the inspiration for this project. The accuracy rate of 99.94% is the performance metric.

WBC Classification using DCNN was suggested by Ming Jiang et al. in 2018. The WBCNet algorithm [9] is used in the work. The 83 percent accuracy rate is used as a performance metric. They employed common deep learning algorithms for Classification of Leukocytes with the help of DNN [10] in this paper. The author, Wei Yu Et.al, who successfully completed this project, released this model in 2017. Performance is measured by the accuracy metric, which will be around 88.5 percent.

3. Methodology

3.1. Components

The proposed work is performed in python with the help of several packages like Tensor Flow, Pandas, Numpy, Matplotlib and Scikit-learn. The entire work is implemented in Google Colaboratory.

3.2. Lymponet

LYMPONET is a new convolutional neural network model which can able to perform the feature extraction and can be used as an image classification model. LYMPONET architecture comprises of 20 layers as five convolution blocks which is used for feature extraction, then followed by a fully connected layers(dense layers). In this work, the architecture is designed to process with RGB images and to train the input images with the shape of (120, 120) and intended to classify four classes.

A convolution layer, a max pooling layer, and a dropout layer make up each convolution block. In a deep CNN, convolutional layers are where the filters are applied to the original picture or other feature maps. When the same filter is applied to an input, it creates a feature map, as well as doing a convolution operation to the input and forwarding the output to the next layer. As a result, a convolution layer multiplies a two-dimensional array of input (picture) by a two-dimensional array of weights (kernel or filter).

As the operation is a dot product, the outcome of this multiplication for one time is a single value. Because the filter is carried out to the input array many times, the outcome is a two-dimensional array of values known as a feature map. The cause of the created filter is to perceive a certain sort of feature within side the input, and then use that filter to methodically series the complete input image, permitting the filter to discover the ones characteristics throughout the image.

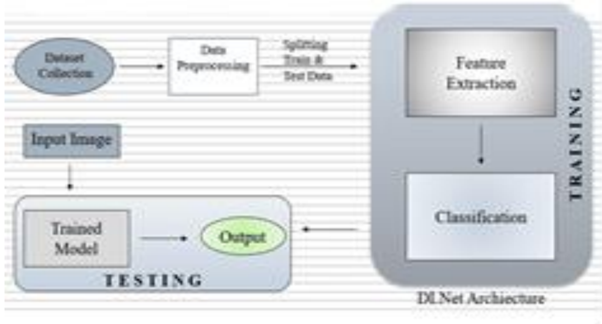

Fig.1. The Image showing the Overview of LYMPONET System.

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Size of the Feature Map / Output Tensor (Image) of a ConV Layer:

O = ((I - K + 2P) / S) + 1

Where,
O denotes the image's output shape.
I denotes the image's input shape
K denotes Kernel size (height / width) in ConV Layers.
S denotes the convolution operation's stride
P stands for padding.

Note: When padding = “same” and strides = 1, the output has the same size as the input.

Number of Parameters of a ConV Layer:

Parameters = ((W * H * D) + 1) * K

Where,
W denotes the filter's width.
H stands for the filter's height.
D - The preceding layer's filter count
K - The current layer's number of filters

The Activation Function determines whether a neuron is active or inactive. The activation function of a neural network tells how the weighted sum of inputs from a node or nodes in a network layer leads to an output from that node or those nodes.

Table 1. Parameter calculations in LYMPONET Architecture

Layer	# Filters/ Neurons	Filter Size	Stride	Tensor Size	Weights	Biases	Parameters
Input	-	-	-	120x120x3	0	0	0
ConV-1	32	3x3	1	120x120x32	864	32	896
MaxPool-1	-	2x2	2	60x60x32	0	0	0
Dropout-1	rate = 0.25	-	-	60x60x32	0	0	0
ConV-2	64	3x3	1	60x60x64	18432	64	18496
MaxPool-2	-	2x2	2	30x30x64	0	0	0
Dropout-2	rate = 0.25	-	-	30x30x64	0	0	0
ConV-3	128	3x3	1	30x30x128	73728	128	73856
MaxPool-3	-	2x2	2	15x15x128	0	0	0
Dropout-3	rate = 0.25	-	-	15x15x128	0	0	0
ConV-4	256	3x3	1	15x15x256	294912	256	295168
MaxPool-4	-	2x2	2	7x7x256	0	0	0
Dropout-4	rate = 0.25	-	-	7x7x256	0	0	0
ConV-5	256	3x3	1	7x7x256	589824	256	590080
MaxPool-5	-	2x2	2	3x3x256	0	0	0
Dropout-5	rate = 0.25	-	-	3x3x256	0	0	0
FC-1	2048	-	-	2048x1	4718592	2048	4720640
Dropout-6	rate = 0.25	-	-	2048x1	0	0	0
FC-2	4	-	-	4x1	8192	4	8196

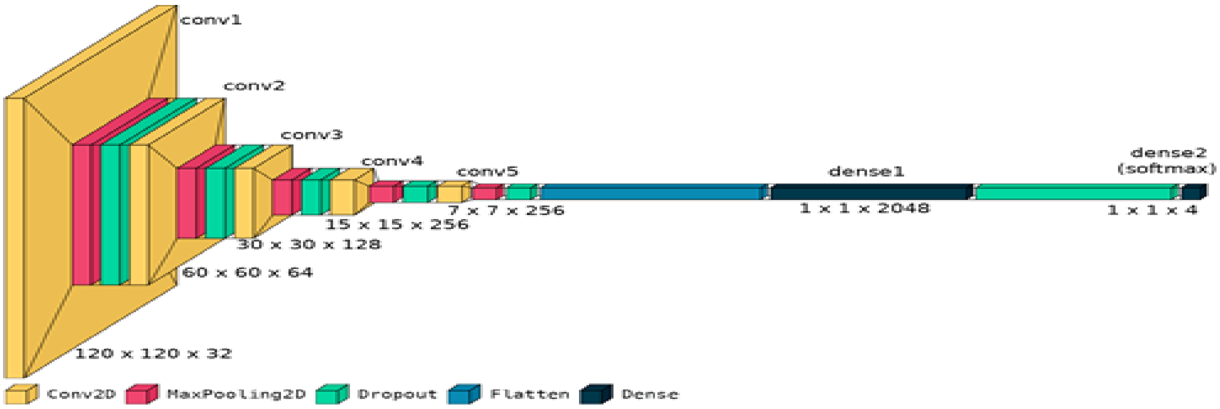

Fig 2. The diagram depicts the Model Architecture Diagram

The pooling layers technique reduces feature map sampling by summarising the existence of features in areas of the feature map. The size of the feature maps are lowered by employing pooling layers. Specifically, after applying a non-linearity (e.g., ReLU) to the feature maps created by a convolutional layer, the pooling layer works on each feature map independently. A new collection of pooled feature maps will be developed.

The pooling procedure includes selecting a pooling operation and filter to apply to feature maps. Both the pooling process and the filter used are less than the size of the feature map.

Size of Output Tensor Image in MaxPool Layer:

Note: When padding = “valid” (no padding)

O = floor ((I - Ps) / S) + 1

Where,
O - Output Shape of the Image
I - Input Shape of the Image
Ps - Pool Size
S - Strides

The dropout approach is used to prevent a model from being overfit. In a neural network, large weights indicate a more complicated network that overfits the training data. It is a simple and effective regularisation approach in which nodes are probabilistically dropped from the network. When using dropout, it's best to have a bigger network with more training and to use the weight constraint.

The five convolution blocks in LYMPONET are composed of CONV layers, which perform 3x3 convolutions (kernel size) with stride as 1 and 'same' padding with ReLU activation, a non-linear activation function, followed by MAXPOOL layers, which perform 2x2 max pooling with stride 2, and with dropout layer with rate of 0.25.

Number of Parameters for Fully Connected (FC) Layer:

Parameters = (C * P) + (1 * C)

Where,
C - Current Layer Neurons
P - Previous Layer Neurons

The overall accuracy of LYMPONET Architecture is observed as 97.5% and the below table depicts the performance metrics of the model.

Table 2. Performance Metrics of LYMPONET Architecture

Blood Cell Type	Precision	Recall	F1 - Score
Eosinophil	0.967	0.951	0.959
Lymphocyte	1.000	0.988	0.994
Monocyte	0.966	1.000	0.983
Neutrophil	0.967	0.964	0.965

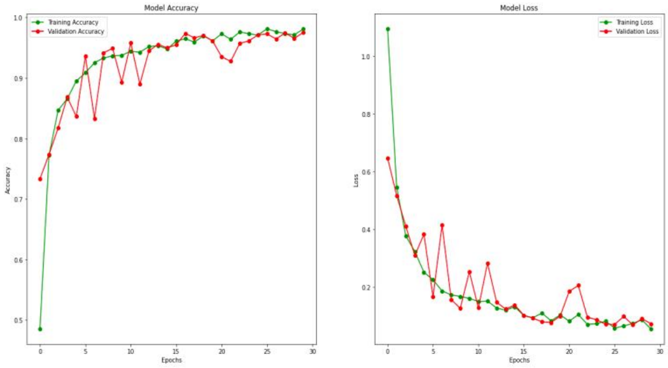

Fig 3. Accuracy and Loss Graph of LYMPONET Model

4. Transfer Learning

Transfer learning stands among the type of machine learning technique that entails making use of a model created for one task to another. Due to the giant useful resource and time desires essential to assemble neural community models on those challenges, in addition to the huge jumps in capacity that they deliver on related concerns, pre-trained models are hired as a place to begin for computer vision and natural language.

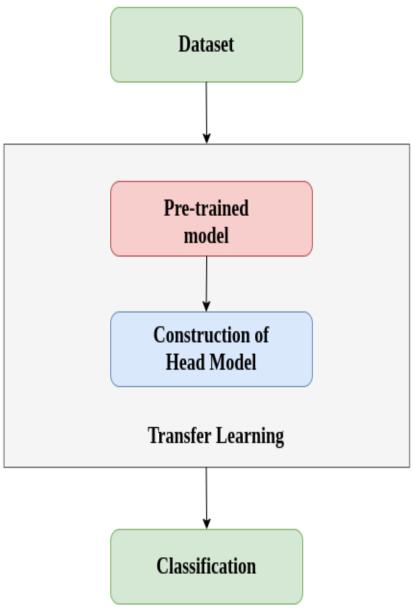

Fig 4. Transfer Learning Work flow

The popular CNN models like VGG16, InceptionV3, Xception, and ResNet152V2 are applied in this work through transfer learning.

The observation of the results for the applied models are described below.

VGG16

VGG16 has attained the overall accuracy as 92.59% and the below table depicts the performance metrics of the model.

Table 3. Performance Metrics of VGG16 model

Blood Cell Type	Precision	Recall	F1 - Score
Eosinophil	0.863	0.883	0.873
Lymphocyte	1.000	0.978	0.989
Monocyte	0.946	0.943	0.945
Neutrophil	0.895	0.898	0.897

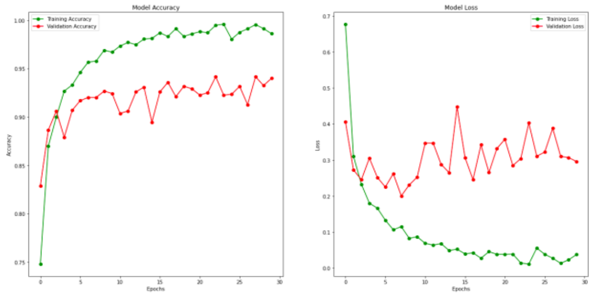

Fig 5. Accuracy and Loss Graph of VGG16 model

InceptionV3

It is observed that InceptionV3 has attained the overall accuracy of 85.59% and the below table depicts the performance metrics of the model.

Table 4. InceptionV3 Model Performance Metrics

Blood Cell Type	Precision	Recall	F1 - Score
Eosinophil	0.772	0.746	0.759
Lymphocyte	0.978	0.925	0.951
Monocyte	0.882	0.963	0.921
Neutrophil	0.802	0.799	0.801

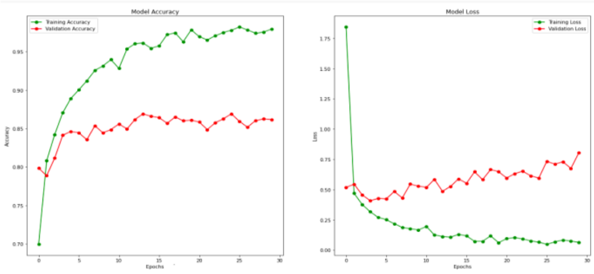

Fig 6. Accuracy and Loss Graph of InceptionV3 model

Xception

Xception has achieved the overall accuracy of 91.11% and the following table describes the performance metrics of the model.

Table 5. Performance metrics of Xcpetion model

Blood Cell Type	Precision	Recall	F1 - Score
Eosinophil	0.812	0.872	0.841
Lymphocyte	0.987	0.991	0.989
Monocyte	0.969	0.952	0.960
Neutrophil	0.877	0.830	0.853

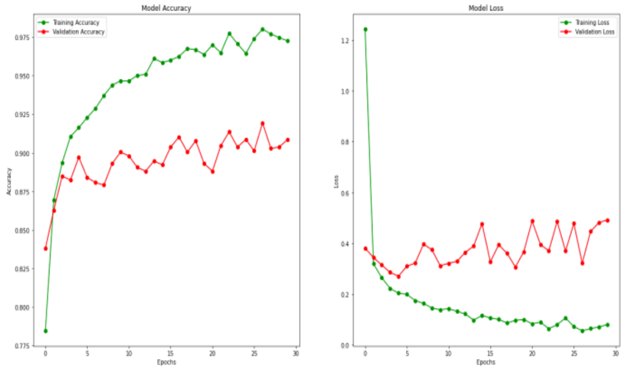

Fig 7. Accuracy and Loss Graph of Xception model

ResNet152V2

The overall accuracy of ResNet152V2 is observed as 93.33% and the following table describes the performance metrics of the model.

Table 6. Performance metrics of ResNet152V2 model

Blood Cell Type	Precision	Recall	F1 - Score
Eosinophil	0.853	0.898	0.875
Lymphocyte	0.997	0.971	0.984
Monocyte	0.983	0.977	0.980
Neutrophil	0.902	0.887	0.894

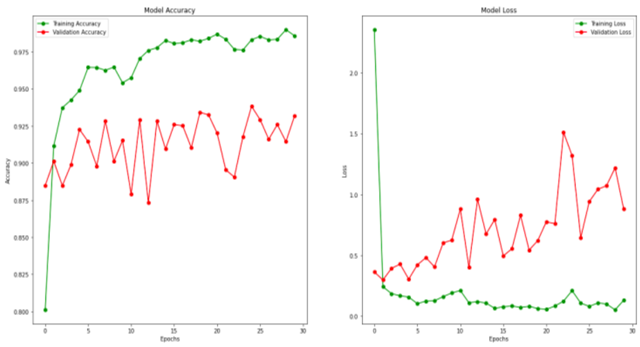

Fig 8. Accuracy and Loss Graph of ResNet152V2 model

5. Conclusion

In this proposed work, we used the LYMPONET architecture, a new convolutional neural network model (custom-built), to classify white blood cells. We found that LYMPONET produced better results when compared to other popular CNN models like VGG16, InceptionV3, Xception, and ResNet152V2, and that the time spent training the LYMPONET model was significantly less than the other models. It's also worth noting that LYMPONET had the greatest overall accuracy of all the architectures used in the study, at 97.5 percent.

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