

# Leukocytes Classification Using Convolutional Neural Network

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## Abstract

Maintaining a healthy life is very important in today's world. Our body has ability to fight against contagious diseases with the aid of white blood corpuscles (WBC) which generates natural immune system. Preserving a good WBC count is crucial as it leads to various hematological problems, one among them is Leukemia, a condition which results in blood cancer, huge accumulation of WBC cells in bone marrow, an abnormal growth of WBC cells, hinders natural immune system fighting against infectious diseases. White blood cells can be categorised into Eosinophils, Lymphocytes, Monocytes, Neutrophils and Basophils. In this study, a pre-trained Convolutional neural network architecture called Le Net is used to automatically classify WBC cells. It efficiently classifies WBC cells from the given input sample blood cell images compared to other pre trained models such as Alex-Net and custom-built CNN called white capsule net. The hyper parameters Le Net are fine tuned to yield higher accuracy of 96%.

## Keywords

CNN, Lymphocytes, Monocytes, Neutrophil, Deep learning, blood cells, LeNet.

## Imprint

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## 1. Introduction

Blood contains different kinds of cells. Blood cells are composed of two broader categories one is RBC (Red Blood corpuscle) Erythrocytes and another one is WBC (White blood corpuscle) Leucocytes and another component is platelets. WBC plays a vital role in human immune system, which fights our body against different diseases whereas Erythrocytes carries oxygen to the tissues and platelets helps to clot blood [1]. A human body has an average of 10 to 12 percentage of Lymphocytes cells, Monocytes occupies 3 to 8 percent of WBC, Neutrophils is about 60 to 70 percentage of WBC, Eosinophils is about 2 to 4 percentage of WBC and Basophils is about 0.01 to 0.3 percentage of WBC. Blood and lymph tissues include WBCs, which are made in the bone marrow. By employing pre-trained CNN models for the structured finding of several white blood cell kinds, this method will extract various white blood cells, including Eosinophils, Lymphocytes, Monocytes, Neutrophils, and Basophils. WBC (white blood cell count) has to be checked periodically for maintaining a healthy immune system [4]. For new born the range should be 9000 to 30000, children under 2 years age 6200 to 17000, for adults and children above 2 years it is 5000 to 10000.

Initially collecting images and splitting it into training and testing set then Pre-Processing the images using Sequential model. Building classification model and predicting the blood cell type. Feature Extraction is to diminish the number of parameters in a dataset by building novel features from the existing ones. Comparison of pre-trained models like Alex Net, Le-Net and White capsule Net

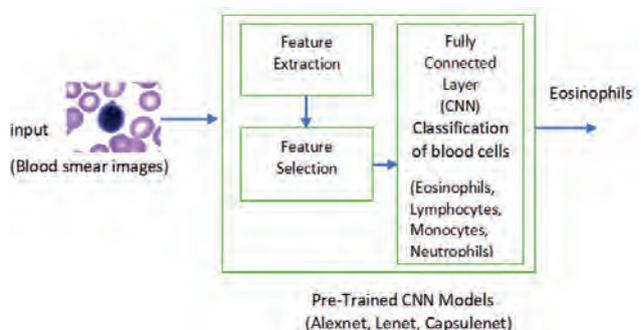


Fig. 1 System Architecture

## II. LITERATURE SURVEY

G. Sharma R. Kumar et al. Proposed a binary and multi class classification problem for WBC classifica-

tion using 5-2D convolutional layers with varying filter size [5]. The size of the dataset is 364 WBC cells. Non-linear digital filter was used to reduce noise in input image. Data is augmented to increase the size of dataset from 364 to 12, 439. It is implemented in MATLAB. Various hyper parameters were considered to get better accuracy of the model. For binary classification the testing accuracy was 99.76% and for multi class it was 98%. The training time is 0.21 sec. Wei Li, et al. [6] Pixel-pair method is used for hyperspectral images where pixel by pixel comparison is done and final result was based on voting policy. The results were good when compared to traditional deep learning methods. The datasets used were Salinas and Indian pines data and university of Pavia. This model was implemented using techniques like K-NN, SVM, ELM and CNN. The accuracy is good for CNN 98.4%. The performance of the overall model was good but with increase in computational cost. Changhun Jung, Etal. [7] Proposed a novel CNN model called W-Net which classifies WBC into 5 classes. It outperforms other CNN models such as VGGNET, Alex Net and RNN models. It uses GAN (generative Adversarial Network) to generate artificial WBC blood sample images which looks similar to original images [8]. The experiment was done on 6562 real images. This model achieved 97% accuracy. Vigueras-guill, et al. [9], this model uses a CNN architecture called capsule networks for classifying WBC cells which overtakes the pre trained models such as ResNeXt-50 which is implemented on public WBC dataset. Different layers of capsules are used to increase the efficiency of the network helps in cell level diagnosis specially to detect blood cancer due to over production of WBC cells. Hyper parameters like optimizers used is Nadam for capsule networks. The training time is more when the number of capsule layers are more. A. Kumar and J. Kim [10], proposed ensemble CNN architecture which extracts rich features from given input image by fine tuning of hyper parameters. LeNet shows higher accuracy when compared to pre-trained CNN models like Alex Net and Google Net. It achieves maximum accuracy on large trained datasets. The dataset used is Image CLEF 2016 medical images. Of size 6776 training and 4166 testing images. Data augmentation was followed to generate more sample datasets of size 67760 similar to real dataset of size 6770. The dimensionality reduction was done by Principal component analysis (PCA). Results from classifiers like SVM and SoftMax are good. On the open BCCD dataset, two DCNN were

used for WBC classification, outperforming VGG16, VGG19, Inception V3, Resnet-50, MLP, DT, and RF by X. Yao, K. Sun, X. Bu, C. Zhao, and Y. Jin et al. [11]. Accuracy was good for low resolution and unbalanced dataset. Ostu segmentation was used. In future a greater number of optimizers can be used to avoid overfitting problem. J. Yao et al. used Faster RCNN and Yolov4 [12] for classifying WBC cells on BCCD dataset. The accuracy obtained by both methods are 96.25% and 95.75%. Data augmentation method called geometric transformation and neural style were adopted to enhance the accuracy of the model. R. Baig, A. Rehman, and A. Almuhaimeed et al. [13] Deep learning-based leukemia detection with hybridized CNN. For image preprocessing 2 methods are followed Image intensity adjustment and adaptive histogram equalization methods. Two CNNs are used to identify exact features needed. Canonical Correlation Analysis is used to concatenate the outputs of two CNNs in order to further identify the most crucial features and increase training duration and effectiveness. Use classification algorithms like SVM, Bagging ensemble, total boosts, RUS Boost, and fine KNN to compare the precision of each classifier. The Bagging ensemble's overall accuracy was 97.04%. A dataset of 4150 images includes three types: Acute Lymphoblastic Leukemia (ALL), Acute Myeloid Leukemia (AML), and Multiple Myeloma (MM). M. Yildirim et al. [14] One of the most widely used neural networks, the convolutional neural network (CNN), is used in this study to distinguish between the eosinophil, lymphocyte, monocyte, and neutrophil types of white blood cells. Before training on the Kaggle Dataset, the CNN was coupled with Alex net, Resnet50, Densenet201, and Google Net. Each image in the database was then separately subjected to the Gaussian and median filters. CNN again categorized the updated images for each of the four networks. The photographs produced better outcomes when the two filters were applied than when the raw data was. The findings of the study facilitate the diagnosis of blood-related illnesses. A Rehman as well as others [15] In stained bone marrow images, this study recommended classifying ALL into its subtypes and reactive bone marrow (normal). Deep learning convolutional neural network techniques are used to train the model using images of bone marrow, which results in accurate classification results. After that, the results of the tests were contrasted with those of the Naive Bayesian, KNN, and SVM classifiers. According to experimental findings, the suggested method has an

accuracy rate of 97.78%. The outcomes demonstrate the recommended approach's potential for use as a diagnostic tool for acute lymphoblastic leukemia and its subtypes, which will surely be useful to pathologists. C. Cheuque et al. [16] provided a more useful hybrid classification scheme for WBC leukemia. It begins by extracting features from WBC images using VGG Net, a powerful CNN architecture that has been trained on ImageNet. A statistically enhanced Salp Swarm Algorithm is then used to filter the extracted features (SESSA). The most important features are selected by this bio-inspired optimization technique after removing highly correlated and noisy features. On two open WBC Leukemia reference datasets, we were successful in achieving good accuracy while simultaneously minimizing computing complexity using the suggested strategy. The SESSA optimization reduced the number of features picked from the 25 K features recovered with VGG Net to 1 K, while concurrently improving accuracy. They outperform a number of convolutional network models and produce some of the top results on these datasets. We anticipate that CNN will merge. The purpose of this work is to develop a computerized [17] WBC categorization system based on deep learning. By optimizing ResNet, Inception, and VGG Net, transfer learning has been incorporated into many of the models that have been proposed so far for this application. The ImageNet dataset on which all of these models were trained is completely unrelated to the dataset utilized in this application. Therefore, we have suggested a deep learning model for the classification of white blood cells without requiring transfer learning.

Diabetes mellitus is a major health issue that affects a large portion of the global population. Diabetes is primarily brought on by ageing, poor eating and sleeping patterns, genetics, and a lack of exercise. Diabetes increases the risk of developing serious health issues like heart disease, renal disease, lung illness, etc. The failure of body organs may occur if diabetes is not effectively managed. Maintaining the patient's health depends on an accurate diabetes diagnosis and treatment. The use of machine learning in the healthcare industry is growing daily. In order to identify diseases, machine learning aids in the extraction of information that is helpful from raw medical data. Artificial neural networks (ANNs) using different batch sizes, epochs, and methods like K-Nearest Neighbor [18].

In recent years, the number of people affected by cardiovascular disorders has increased. The condition

is accelerated by a sedentary lifestyle, specific genetic factors, obesity, inactivity, and stressful work settings. One of the cardiovascular disorders caused by inadequate blood flow and oxygen levels in the circulation is heart failure. Machine learning techniques are used by researchers to pinpoint the key components of cardiac disorders [19].

A lung infection called pneumonia is brought on by bacteria. A prompt diagnosis is necessary for effective treatment. Typically, chest x-ray pictures can be used to identify the condition by a skilled radiologist. Making a diagnosis may be difficult for a number of reasons, including the disease's appearance on chest x-ray pictures or other confounding factors. For clinicians, CAD (computer-aided diagnostic) systems are advantageous for this reason. Well-known convolutional neural network models utilized in the diagnosis of pneumonia include VGG16 and Xception [20].

The drug discovery process is expensive and time-consuming in the pharmaceutical sector. Even more time may be needed for the pre-clinical process. The data on millions of medications is stored in a number of drug repositories. Researchers worldwide constantly create novel chemicals and investigate their potential as pharmaceuticals. The second round of testing would involve the medication administration route, even though its disease-inhibiting properties are identified in the first stage. At this stage, the method of administration, such as Oral, Parenteral, and Topical, is identified [21].

With the use of X-rays or computer tomography (CT) scans, a deep learning technique known as Deep Convolution Neural Network (DCNN) is employed as a tool to detect COVID-19 infected patients as a result of technical breakthroughs in the field of AI. The picture data from internet sources like Kaggle, GitHub, and other websites, such as X-ray and CT scan data, are trained using a variety of DCNN models. It has been demonstrated that Deep Convolutional Generative Adversarial Network (DCGAN), one of the GAN variations, can handle an unbalanced picture dataset effectively (Generative Adversarial Network). Only if the dataset is substantial enough to increase training efficiency will training be effective [22].

Sickle Red blood cells (SRBC) are defective RBCs that have undergone an aberration, changing from the normal, disc-shaped cells that they were inherited with to the atypical, sickle-shaped cells. The majority of RBCs undergo a significant change in nature

that causes them to become sticky, hard, and crescent-shaped cells, which makes them difficult to pass through very small blood capillaries and restricts the normal flow of blood by plugging or closing the blood vessels. A red blood cell (RBC) transforms into a sickle RBC (SRBC) when the amount of hemoglobin A (HgbA), which is typically present in a normal RBC cell, decreases [23].

### III. DATASET DESCRIPTION

It consists of 2000 images of the leukocyte cells (Neutrophil, Eosinophils, Lymphocytes, monocytes) taken from the publicly available from dataset. The size of the images should be 320\*240. The given input image from the dataset is preprocessed. Data augmentation techniques like cropping, resizing and normalizing the given blood cell image. Train the model for feature extraction and selection for taking only necessary feature required from the image to predict the exact type of cell. Finally, by comparing the 3 modules (White Capsule Net, Alex-Net and Le-Net) which are pre-trained models detects cell type accurately from the given input image and predicts the correct type of leukocyte cells and produce the output. This dataset includes 376 test image records and about 2000 train image records with extracted features, which were then classified into 4 classes:

1. Eosinophils
2. Lymphocytes
3. Neutrophils
4. Monocytes

Deep learning-based leukocyte classification using Convolutional neural network algorithm is very efficient in analyzing different types of WBC. The different layers in CNN processes the input image and predicts the exact output. The kernel in CNN first extracts the relevant features of the input image called feature map, needed for prediction. The next layer in CNN called pooling layer selects largest, further processes the images to reduce dimensionality of convolved input image (feature map) using one of the kind of pooling layer called max pool layer which decreases computational cost. The pooling layer sits between convolutional layer and fully connected layer (FC). Fully connected layer with weights biases and neurons is placed before the output layer. The fully connected layer connects neurons of two different layers. The actual classification of input image is performed here.

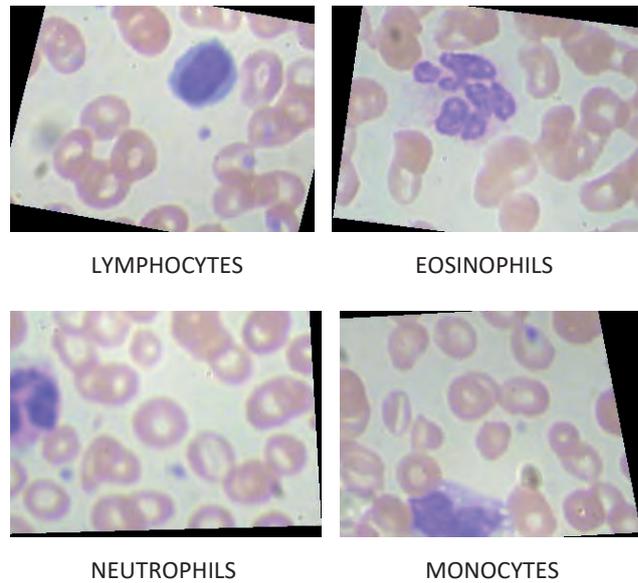


Fig 2. Types of Leucocytes

utilizing the data generator preprocessing function in Keras, which carries out actions on the data to enhance it, such as size, rescale, range, zoom range, and horizontal flip. Then use the data generator tool to import the folder containing the preprocessed image dataset. In order to build a new CNN model using pre-trained models that already exist,. The following parameters training, testing, validation setting target size, batch size, class-mode and adding layers to CNN can be customized from this function so that a new CNN model can be created from already existing pre trained models.

### IV. EXTRACTION OF FEATURES AND FEATURE SELECTION

The method of feature extraction involves turning unprocessed raw data into numerical features that may be handled while keeping the original data set's content. It generates superior results when compared to utilizing machine learning on the raw data directly. The choice of the appropriate diagnostic feature is crucial for pattern recognition. Using the texture, geometrical, and statistical analysis of the image to describe the image using numerical values and enable the automatic system to conduct the recognition. After that, features were extracted utilizing the feature fusion of pointwise in 2D CNN Convolutional layer. By using only pertinent data, feature selection helps to limit the number of input variables for the model. When creating a predictive model, it reduces the amount of input variables.

## V. PRE-TRAINED CNN MODELS

### A. Alex Net

The medical sector is significantly impacted by one of the pre-trained convolutional neural network models, Alex-Net, notably in the application of deep learning. The first convolutional neural network model to use a graphics processing unit (GPU) to boost network performance was Alex-Net. Various convolutional layers, max-pooling layers, normalizing layers, fully linked layers, and a SoftMax layer make up the Alex-Net architecture. The nonlinear activation function RELU and convolutional filters are both present in every convolutional layer. Max pooling is carried out using the pooling layers.

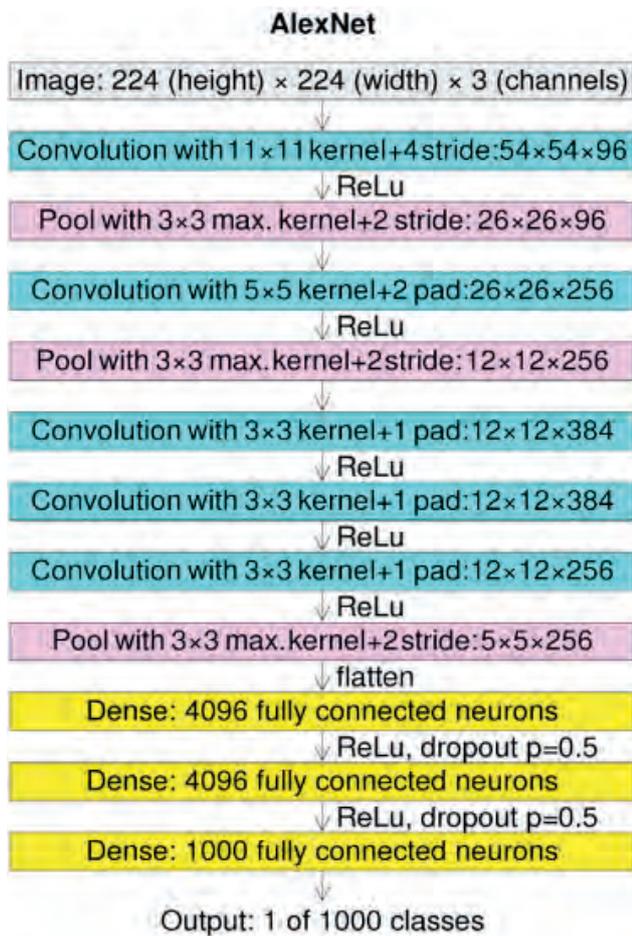


Fig 3. Architecture of Alex Net

### B. LeNet

The result of multiple fascinating iterations was Le-Net. Seven layers make up the LeNet-5 CNN's architecture. The layer composition includes Le-Net, one of the earliest convolutional neural networks, because it advanced deep learning. Le-Net was the name given to the finished product after extensive analysis and numerous convincing itera-

tions. Seven layers make up the LeNet-5 CNN's architecture. The layer composition consists of 3 convolutional layers, 2 subsampling layers, and 2 fully linked layers.

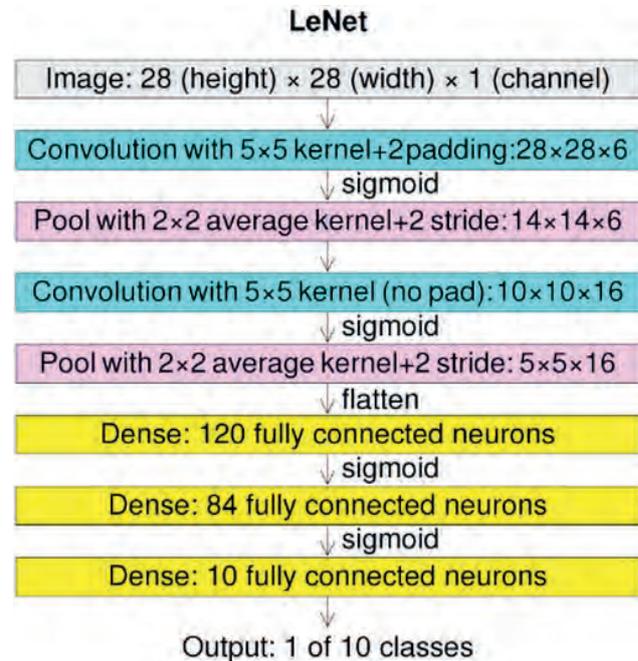


Fig 4. Architecture of LeNET

### VI. Final Layer of CNN

Prior to classification, the data are flattened using fully linked layers, which make up the last layer in CNN. This is equivalent to the output layer of a multilayer perceptron. In the completely connected layer, neurons, weights, and biases are present. To categorize photos into distinct groups, training is utilized. The output of the preceding layers in the picture below is "flattened" by the flatten layer into a single vector that can be used as an input in the following step. The outputs of pooled feature maps, which are presented as 2-Dimensional arrays, are all flattened into a single, substantial continuous linear vector. The fully linked layer, which classifies the image, receives the flattened matrix as input.

### VII. Statistical Analysis

A table called a confusion matrix is often used to summarize how well a classification model, also known as a "classifier," performed on a set of test data for which the true values were known. Were,

A true positive is a TP.

True Negative (TN), False Positive (FP), and False Negative, or FN

		Actual Values	
		Positive (1)	Negative (0)
Predicted Values	Positive (1)	TP	FP
	Negative (0)	FN	TN

Fig 5. Matrices of Actual Values

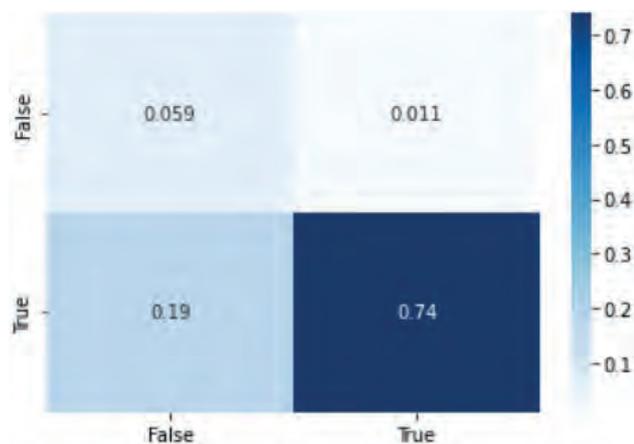


Fig 6. Probability of predicting positive and negative cases

Leukocyte images show

74% are TPs, or true positives.

11 percent are false positives, or FPs.

19% of the data is True Negative.

False negatives make up 59% of the data.

### (i) Accuracy

Based on the input, or training, data, accuracy is a metric used to determine which neural network model is effective at identifying relationships and patterns between variables in a dataset. The following formula should be used to determine accuracy:

$$(T_1P_1 + T_1N_1 / ((T_1P_1 + T_1N_1) + (F_1P_1 + F_1N_1)))$$

In this model, classification accuracy is 56% accurate.

Which neural network model is effective at identifying relationships and patterns between variables in a dataset is determined by accuracy, a metric.

### (iii) Precision

Precision is one metric used to assess a machine learning model's efficacy. It is a characteristic of an accurate model prediction.

The following formula should be used to determine precision:

$$TP / TP + FP$$

This model's overall accuracy is **0.84761**.

### iv) Recall

The proportion of accurately predicted positive outcomes to all positively expected outcomes.

The following formula should be used to determine recall:

$$TP \text{ and } TP \text{ plus } FN$$

This model has an overall recall of **0.2367**.

### iv) F1 Score

Precision and recall are represented by the harmonic mean of the F1 Score. False positives and false negatives are also taken into account.

Accuracy	: 56.1170220375061
confusion matrix	: [[89.0, 16.0], [287.0, 1112.0]]
precision score	: 0.8476190567016602
Recall and sensitivity score	: 0.23670212924480438
F1 score	: 0.3700623728653426
Specificity	: 17.0

The confusion matrix is used to determine the true positive, true negative, false positive, and false negative values, which makes it simple to distinguish between the model's classifications. The formula for calculating F1 Score is

$$2 * (Precision * Recall) / (Precision + Recall).$$

This model's F1 Score is **0.3700**.

## VIII. White Capsule Net

There are two layers in the White Capsule Net architecture. Max pooling layer and one convolutional layer make up the layer composition. This is a base model that will be used to train and test the dataset's images in order to determine the accuracy and identify the different types of leukocytes (Eosinophil, Lymphocyte, Monocyte, and Neutrophil). Epochs run the batch size in a very short length of time and produce findings right away because this architecture just has two layers. The key advantage is that it is more accurate than Alex-Net and takes a lot more time.

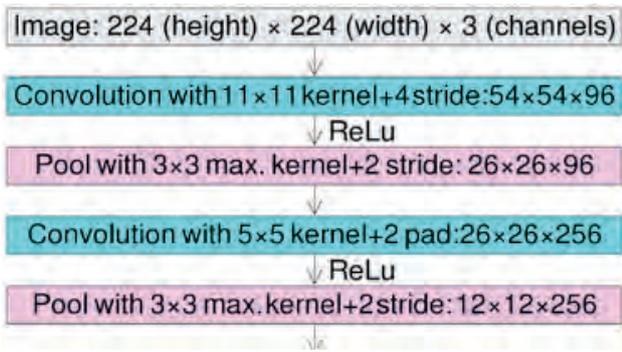
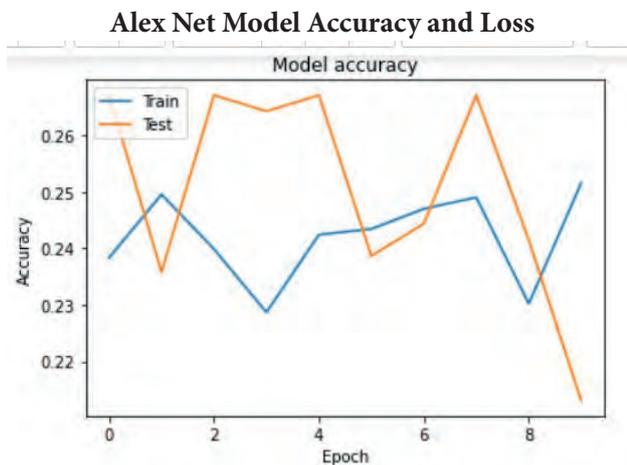


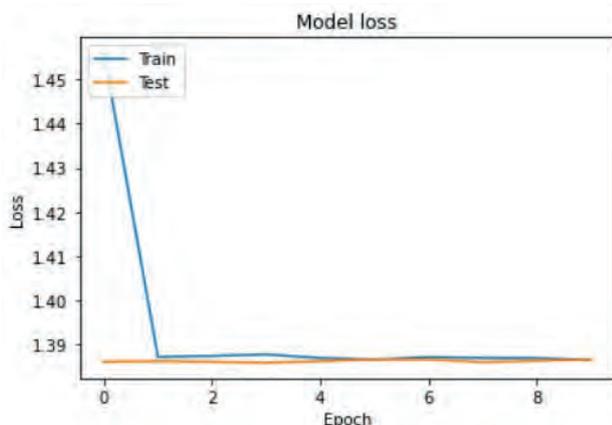
Fig. 7 Architecture of White capsule Net

### IX. Results

By comparing the various CNN Architectures, based on their accuracy and loss, The graphical representation for ALEX-NET is shown in fig. 8 and fig. 9.



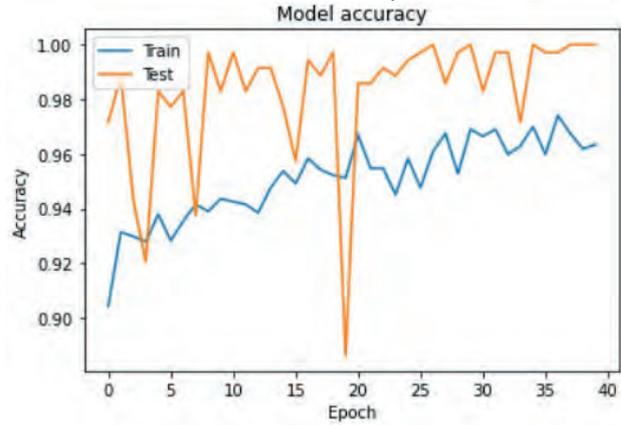
Graph 1. Accuracy Graph



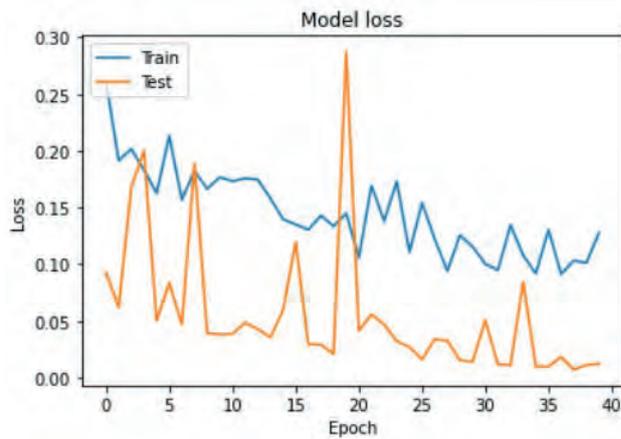
Graph 2. Loss Graph

Accuracy is very important in detecting right type of blood cells. Here comparison of pre-trained algorithms and obtained the results for Alex-Net which gives 25% of accuracy and loss.

### LeNet Model Accuracy and Loss



Graph 3. Graph of Accuracy

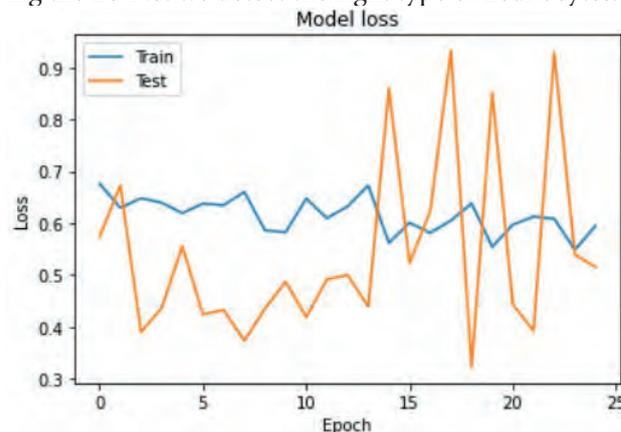


Graph 4. Model Loss

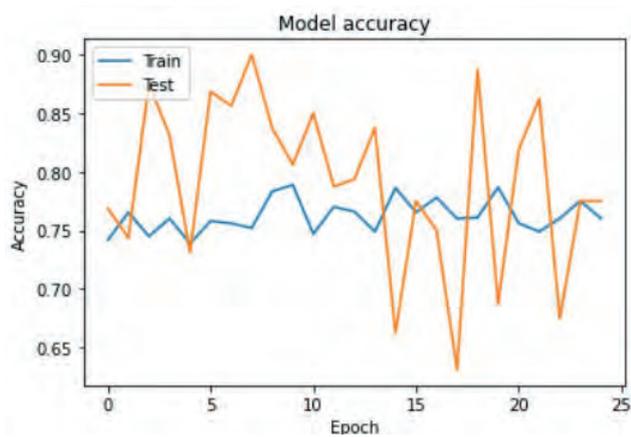
In LeNet model the accuracy is 96% in testing images and loss is 0.1279. This Pre-trained model gives more accuracy by comparing with others. In existing system, they have used MGCNN which yielded 94% of accuracy. In this model we have achieved more than the existing model.

### XI. ACCURACY OF WHITE CAPSULE NET

In White capsule Net the accuracy is 73% and loss is 0.664. Therefore by comparing all the three algorithms Le-Net yields more accuracy with less loss hence by using the Le-Net we detect the right type of Leukocytes.



Graph 5. White Capsule Net Model Loss



Graph 6. White Capsule Net Model Accuracy

## X. Conclusion

In this study, deep learning approaches were created to identify the different types of leukocytes from static cell photos. This is a challenging issue that has already been addressed multiple times using various methods. While feature engineering has produced successful outcomes, this study focuses on feature learning, one of deep learning's promises. Although it is not required, feature engineering, image pre-processing improves classification accuracy. As a result, it lessens input data noise. Nowadays, feature engineering is used in blood cell identification software. A fully feature learning-based solution does not yet seem to be close due to a significant restriction. As a result, deep learning might be used to categorize blood cells.

## XI. Future Enhancement

The following methods can be used to further improve the network's generality and correctness. The optimization is first carried out utilizing the complete dataset. Larger datasets are more suited for batch optimization. A other method is to assess each blood cell separately. This can help determine which varieties are more challenging to categorize. Finally, using a larger dataset for training seems to be beneficial. It's probable that there isn't currently such a dataset. The use of numerous datasets might be a solution, but standardizing them calls for careful thought. A larger dataset and pre-training on specific blood cells appear to have the ability to improve the network's performance. Future studies should therefore concentrate on them.

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