Multiclass Classification of White Blood Cells from Histological Images using Deep Convolutional Neural Networks

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ABSTRACT

The white blood cell (WBC), also called leukocytes, is a cellular component of the blood with a nucleus and without a hemoglobin. As an essential part of the immune system, it moves from blood to tissue and provide defence for fighting against the invasion of the foreign microorganisms, e.g., bacteria, viruses, and germs, by ingesting them, destroying infectious agents or by producing antibodies. Usually, the automatic classification approaches are present with several main steps: preprocessing, segmentation, feature extraction and classification. The preprocessing procedure primarily refers to the attempt of removing the noises or some artifacts from the images to output the contrast images. The segmentation can be considered as the operation of segmenting the WBC from the background of the smear images or extracting the region of interest (ROI). The consequent step is to build a representative feature vector for every type of WBC, and the classification will work based on it. In this very step, the hematologist sometimes may be involved to determine the features. However, the traditional classification approaches consume more time with the compromise in accuracy too. Recent years, the emerging field of deep learning has powered many successful real-life applications. Deep neural networks, particularly convolutional neural networks (CNNs), have been widely applied to perform computer vision tasks such as image classification. Compared to machine learning algorithms, which use hand-crafted features as inputs, CNNs typically take raw images as inputs and learn hierarchical feature representations in an end-to-end fashion. Therefore, this project aimed to implement the detection of subtype blood cells using the advancement of neural networks known as deep learning CNN.

Keywords: White blood cells, histological images, region of interest, deep learning.

1. INTRODUCTION

Blood is a specialized body fluid. Its main components are red blood cells, plasma, platelets, and white blood cells. WBCs protect the body from infections, accounting for about 1% of human blood [1]. Basophils, Eosinophils, Lymphocytes, Monocytes, and Neutrophils are the types of white blood cells, Basophils white blood cells accounting only around 1%, they are important in mounting a nonspecific immune response to pathogens. Eosinophils play an important role in fighting bacteria and responding to infections with parasites. Lymphocytes are also very important in the immune system, they are 2 types: B and T lymphocytes, with B cells producing antibodies, T cells being responsible for directly killing many foreign invaders. Monocytes are responsible for cleaning up dead cells. Roughly half of the white blood cells are Neutrophils; they are usually the first cells of the immune system to respond to an invader such as a bacterium or a virus [2]. White blood cells (WBCs) classification is an important step because it can assist hematologists in the diagnosis of several blood disorders, such as leukemia, some immunological disorders, and certain types of cancer. The analysis procedure can be done by automatic and manual approaches to count and classify WBC. The manual classification of WBC has many medical difficulties, including error in the accuracy of results due to sampling errors and statistical probabilities and poor sensitivity, specificity, and predictive values.

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Furthermore, some automatic approaches in the laboratories have used instruments, such as flow cytometry and automatic counting machine to detect and classify WBC. These instruments do not make use of image processing techniques, and they can count and classify WBCs quantitatively not qualitatively. Therefore, it is necessary to design an automatic system which includes computer-based systems for classification of WBCs.

Researchers are increasingly interested in the development of algorithms for automated analysis of medical images such as microscopic blood smear images. They are using different correlated techniques like; image processing, computer vision, artificial neural networks, machine learning algorithms, etc. [3]. To overcome all these problems, we added the help of CNN to image processing. In this framework, we present a RBC image analysis with the convolution neural network (CNN). CNN is a strong image classifer tool, in which image is taken as input, classify it under certain categories based on their features. In CNN, an individual unit is called a neuron. Neurons are in a series of layers. Neurons of one layer are connected to the neurons of the next layer. Each neuron or node of one layer perform mathematical calculation and pass the results to the next node. The last layer of the neural network has increased computational power due to the accumulation of experience.

2. LITERATURE SURVEY

Alzubaidi et al. [4] introduced a new robust and effective deep Convolutional Neural Network to classify Red Blood Cells (RBCs) in three classes namely: normal (‘N’) abnormal (sickle cells anemia type (‘S’)) and miscellaneous (‘M’). To improve the results further, we have used this model as features extractor then this work applied an error-correcting output codes (ECOC) classifier for the classification task. This model with ECOC showed outstanding performance and high accuracy of 92.06%.

Rahman et al. [5] experimented the existing standard pre-processing techniques from the literature. In addition, several other complex architectures have been implemented and tested to pick the best performing model. A holdout test has also been conducted to verify how well the proposed model generalizes on unseen data. This best model achieved an accuracy of almost 97.77%.

Roopa et al. [6] demonstrated classification of white blood cells into six types namely lymphocytes, monocytes, neutrophils, eosinophils, basophils and abnormal cells. This work provided the comparison of traditional image processing approach and deep learning methods for classification of white blood cells. This work also evaluated neural network classifier results for hand-crafted features and obtained the average accuracy of 99.8%. And used full training and transfer learning approaches of convolutional neural network for the classification. An accuracy around 99% was obtained for full training CNN.

Malkawi et al. [7] classified the microscopic WBCs images using a hybrid system where Convolutional Neural Network (CNN) used as features extractor and different machine learning algorithms used as classifiers, then the performances of these classifiers were evaluated to recognize the best of them. These algorithms included Support Vector Machine (SVM), k-Nearest Neighbor (KNN) and Random Forest, for training and test parameters this framework used five features that were extracted from the images. According to results of performance, the RF performed better than the other methods with a testing accuracy reached 98.7%.

Matek et al. [8] compiled an annotated image dataset of over 18,000 white blood cells, use it to train a convolutional neural network for leukocyte classification and evaluate the network’s performance by comparing to inter- and intra-expert variability. The network classified the most important cell types with high accuracy. It also allows us to decide two clinically relevant questions with human-level

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performance: (1) if a given cell has blast character and (2) if it belongs to the cell types normally present in non-pathological blood smears. This framework approach holds the potential to be used as a classification aid for examining much larger numbers of cells in a smear than can usually be done by a human expert. This will allow clinicians to recognize malignant cell populations with lower prevalence at an earlier stage of the disease.

Sadafi et al. [9] presented an active learning framework that identifies the most relevant samples from a large set of not annotated data for further expert annotation. Applied to brightfield images of red blood cells with seven subtypes, this work trained a faster R-CNN for single cell identification and classification, calculate a novel confidence score using dropout variational inference and select relevant images for annotation based on (i) the confidence of the single cell detection and (ii) the rareness of the classes contained in the image. This framework showed that this approach leads to a drastic increase of prediction accuracy with already few annotated images. This original approach improves classification of red blood cell subtypes and speeds up the annotation. This important step in diagnosing blood diseases will profit from our framework as well as many other clinical challenges that suffer from the lack of annotated training data.

Parab et al. [10] utilized the algorithm which can extract the feature of each segmented cell image and classify it into 9 various types. Images of blood slides were collected from the hospital. The overall accuracy was 98.5%. The system has been developed to provide accurate and fast results that can save patients' lives.

Paravil et al. [11] tried to devise a methodology for automation by using feature fusion. For feature extraction, various fusion techniques using transfer-learning approaches such as Densely connected convoluted neural networks (DenseNet201) and VGG16 (Visual Geometry Group 2016) were proposed. The classification results are compared using various performance metrics such as Accuracy, Precision, Recall, and F1-Score. The maximum accuracy of 89.75% was obtained with the help of feature fusion combined with the Convolutional Neural Network (CNN) classifier.

Yildirim et al. [12] proposed one of the most popular neural networks, convolutional neural network (CNN) is selected to differentiate between different types of white blood cells, namely, eosinophil, lymphocyte, monocyte and neutrophil. The CNN was coupled with Alexnet, Resnet50, Densenet201 and GoogleNet in turn, and trained with the Kaggle Dataset. Then, Gaussian, and median filters were applied separately to the images in the database. The new images were classified again by the CNN with each of the four networks. The results obtained after applying the two filters to the images were better than the results obtained with the original data. The research results make it easier to diagnose blood related diseases.

3. EXISTING SYSTEM

ML falls under the larger canvas of Artificial Intelligence. ML seeks to build intelligent systems or machines that can automatically learn and train themselves through experience, without being explicitly programmed or requiring any human intervention. In this sense, ML is a continuously evolving activity. It aims to understand the data structure of the dataset at hand and accommodate the data into ML models that can be used by companies and organizations. Following are the benefits of ML.

- Enhanced decision-making: ML uses advanced algorithms to improve the decision-making process capacity. It facilitates innovative models and business services simultaneously. It provides a deep understanding of the variations and types of data patterns. You can determine which step to take next based on the variations and data patterns.

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- Increases business productivity: It improves the business process and productivity, contributing to business growth. It helps you to adapt to the changing situations at workplaces quickly. The data continue to be updated daily. So, the work environment, too, keeps on changing quickly. ML reduces the chances of error occurrence by half. Hence, it boosts business productivity. This aspect is important to consider when carrying out deep learning vs neural network.
- Removes manual data entry: One of the most common concerns in many organizations is the usage of duplicate records. ML algorithms use predictive models that significantly avoid any errors caused by manual data entry. The corresponding programs use the discovered data to enhance these processes. Hence, the employees can save time to focus on other important business tasks.
- Guarantees customer satisfaction: The ML algorithms are uniquely designed to continue attaining experience with time. They are accurate and efficient. These algorithms improve the machines' decision-making skills. ML can anyhow find a way to make accurate decisions or predictions, although the data is overwhelming and ever-increasing. It benefits businesses with the latest market opportunities related to revenue. As a result, it can satisfy the customers' expectations and boost your business' sales in less time. Moreover, it can quickly recognize threats in the market. You can compare deep learning vs neural networks based on this aspect to have a clear judgment.
- Provides product recommendation: Unsupervised research assists in the development of suggestion systems depending on goods. Currently, most e-commerce platforms use ML to provide product recommendations. ML algorithms use the consumers' purchasing experience to balance it with the assets' huge inventory. This helps in detecting secret trends and connects identical products. Finally, these goods are recommended to the consumers.
- Detects spam: ML is widely used for spam detection. It uses spam filters to identify spam and phishing communications.
- Improves network security: ML improves an organization's security. It helps organizations to develop new systems capable of quickly and efficiently recognizing unknown threats. It can track abnormalities present in network activity and automatically execute relevant actions. When the ML algorithm is used for self-training, it removes manual research and analysis. So, it enhances the organization's network security. Many deep learning neural networks are also used for this purpose.
- Simplifies business analysis: ML is used in business analysis that involves huge volumes of precise and quantitative historical data. It is widely used for algorithmic trading, portfolio management, fraud detection, and lending in finance. The future ML applications for finance will entail Chatbots and a few other interfaces for improving customer service, security, and sentiment analysis. Many neural networks and deep learning algorithms are also used to streamline finance analysis.

3.1 Disadvantages

- ML Model makes decisions based on what it has learnt from the data. As a result, while ML models may learn from data, they may need some human interaction in the early stages.
- Moreover, its performance is poor with large dataset.

4. PROPOSED SYSTEM

To implement this project, we have designed following modules.

1) Upload WBC Dataset: using this module we will upload entire dataset to application.
2) Pre-process Dataset: using this module we will read train and test images and then resize all images to equal size, shuffle and normalize images.
3) Train Decision Tree: using this module we will train decision tree algorithm on training dataset and then test its performance using TEST images.
4) Train Deep CNN model: using this module we will train CNN algorithm on training dataset and then test its performance using TEST images.
5) Classification: using this module we will input test images and then CNN will classify its subtype blood cell.
6) Performance Evaluation: using this module we will plot accuracy comparison graph between both algorithms.

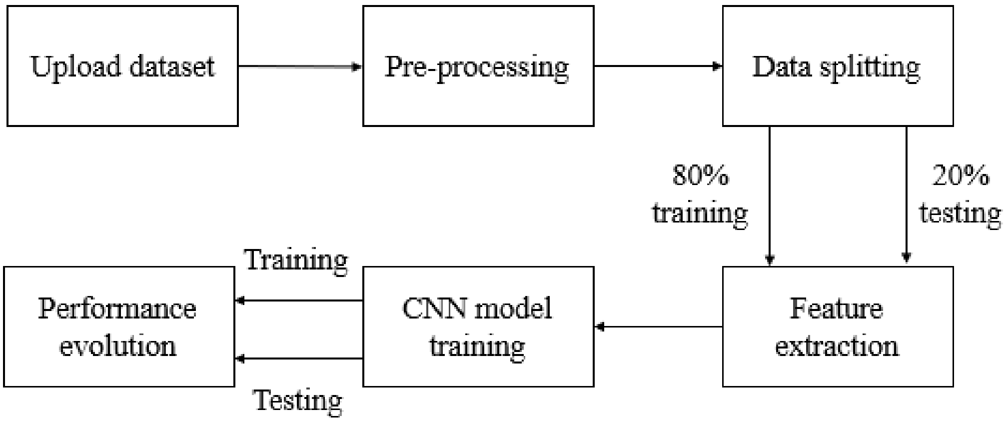

Fig. 1: Block diagram of proposed system.

4.1 Pre-processing

Data pre-processing is a process of preparing the raw data and making it suitable for a machine learning model. It is the first and crucial step while creating a machine learning model.

When creating a project, it is not always a case that we come across the clean and formatted data. And while doing any operation with data, it is mandatory to clean it and put in a formatted way. So, for this, we use data pre-processing task.

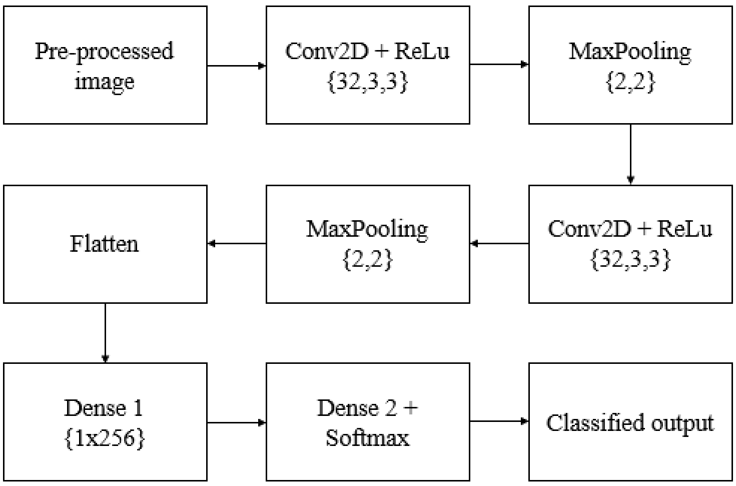

Fig. 2: CNN architecture.

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4.2 DL-CNN

According to the facts, training and testing of any deep neural network or transfer learning involves in allowing every source image via a succession of convolution layers by a kernel or filter, rectified linear unit (ReLU), max pooling, fully connected layer and utilize SoftMax layer with classification layer to categorize the objects with probabilistic values ranging from [0,1].

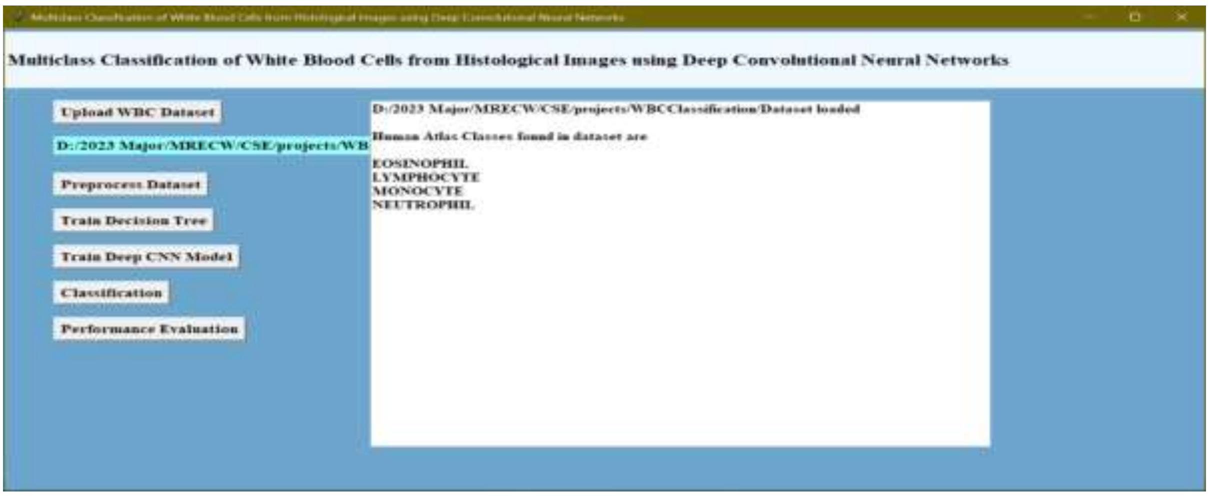
Convolution layer as is the primary layer to extract the features from a source image and maintains the relationship between pixels by learning the features of image by employing tiny blocks of source data. It's a mathematical function which considers two inputs like source image $I(x, y, d)$ where x and y denotes the spatial coordinates i.e., number of rows and columns. d is denoted as dimension of an image (here $d = 3$, since the source image is RGB) and a filter or kernel with similar size of input image and can be denoted as $F(k_x, k_y, d)$.

The output obtained from convolution process of input image and filter has a size of $C\left((x - k_x + 1), \left(y - k_y + 1\right), 1\right)$, which is referred as feature map. Let us assume an input image with a size of 5×5 and the filter having the size of 3×3. The feature map of input image is obtained by multiplying the input image values with the filter values.

Advantages of proposed system

- CNNs do not require human supervision for the task of identifying important features.
- They are very accurate at image recognition and classification.
- Weight sharing is another major advantage of CNNs.
- Convolutional neural networks also minimize computation in comparison with a regular neural network.
- CNNs make use of the same knowledge across all image locations.

5. RESULTS AND DISCUSSION



In above screen dataset loaded and then displaying different classes found in dataset and now click on 'Preprocess Dataset' button to process images and get below output

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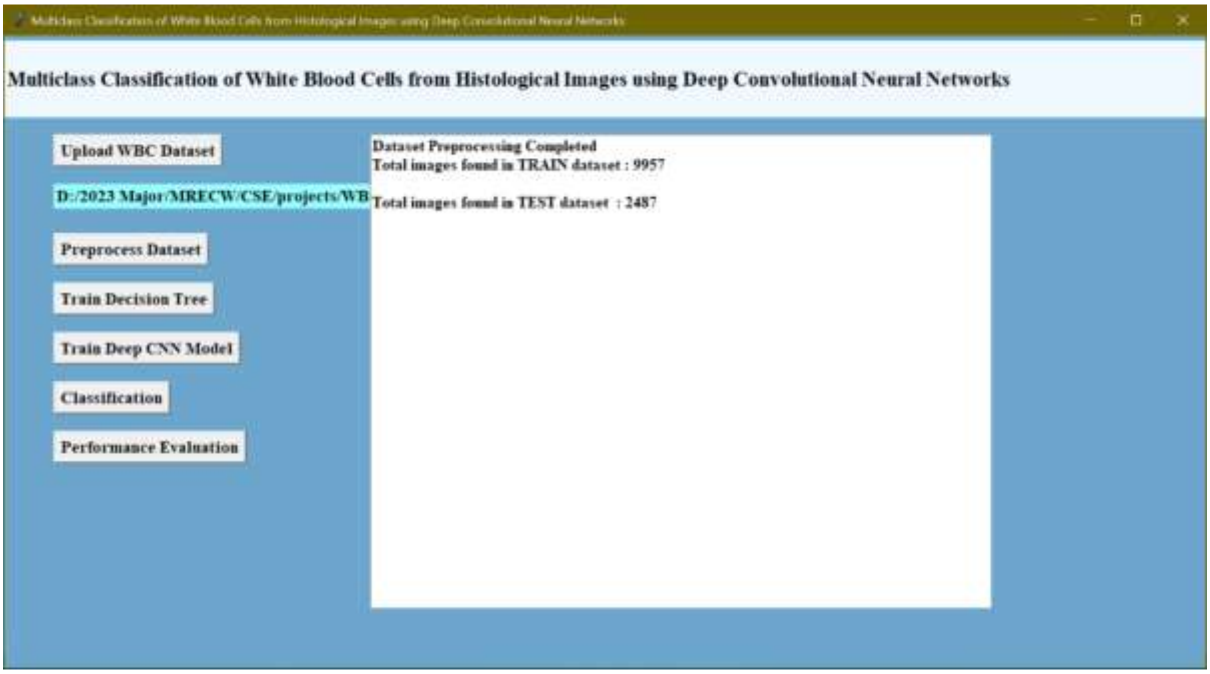
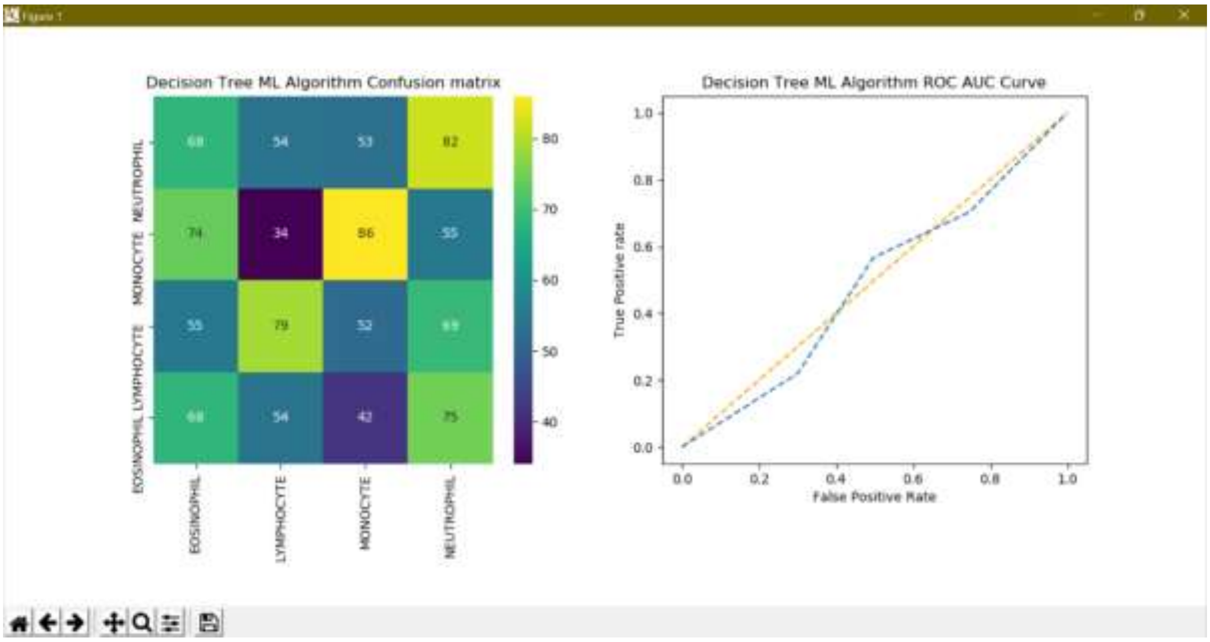
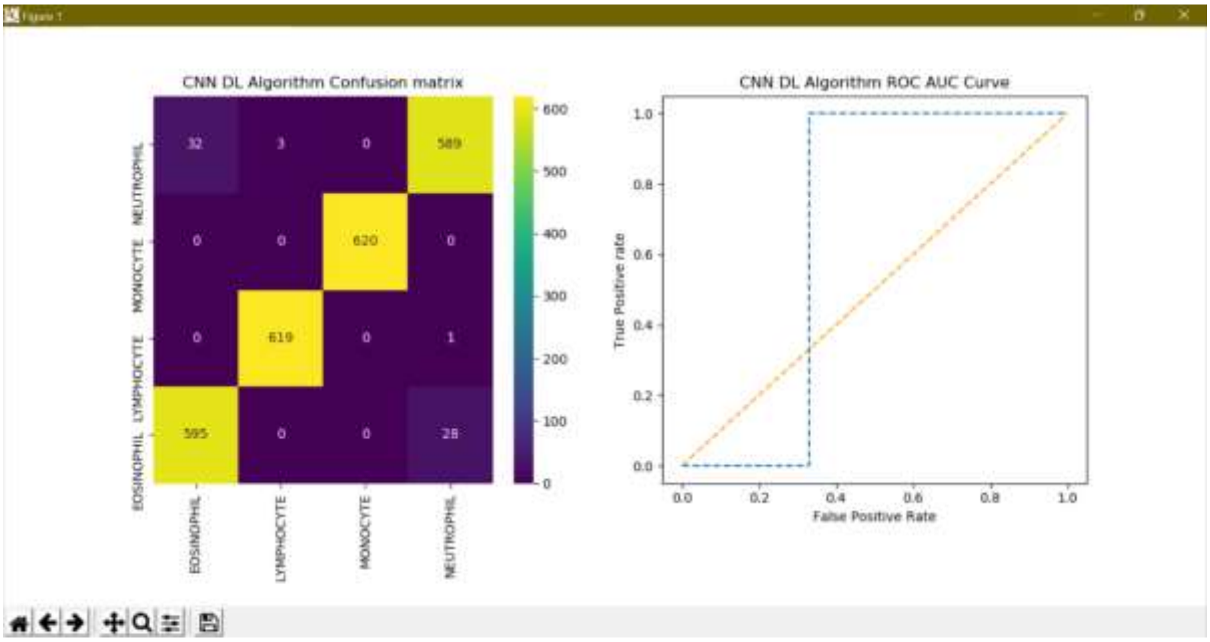


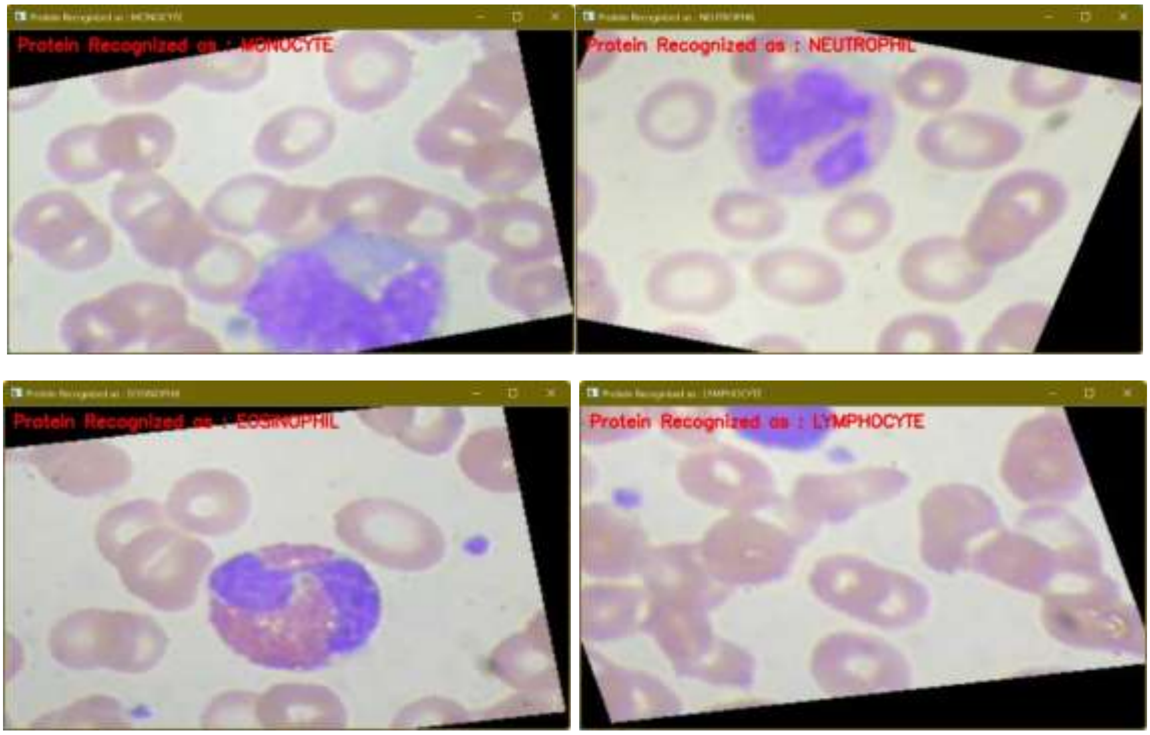
In above screen both train and test images loaded and then displaying sample processed images.



In above confusion matrix graph x-axis represents Predicted Labels and y-axis represents True labels and the count with same label in x and y-axis represents correct prediction count and other boxes represents incorrect prediction count. In above ROC graph x-axis represents False positive rate and y-axis represents True positive rate and if blue line comes below orange line, then prediction is False and if comes on top of orange line then prediction True.



In above screen with CNN, we got 97% accuracy, and we can see confusion and ROC graph also. Now click on 'Classification' button to upload test image and get prediction



In above image, we can see the predicted output on test images.

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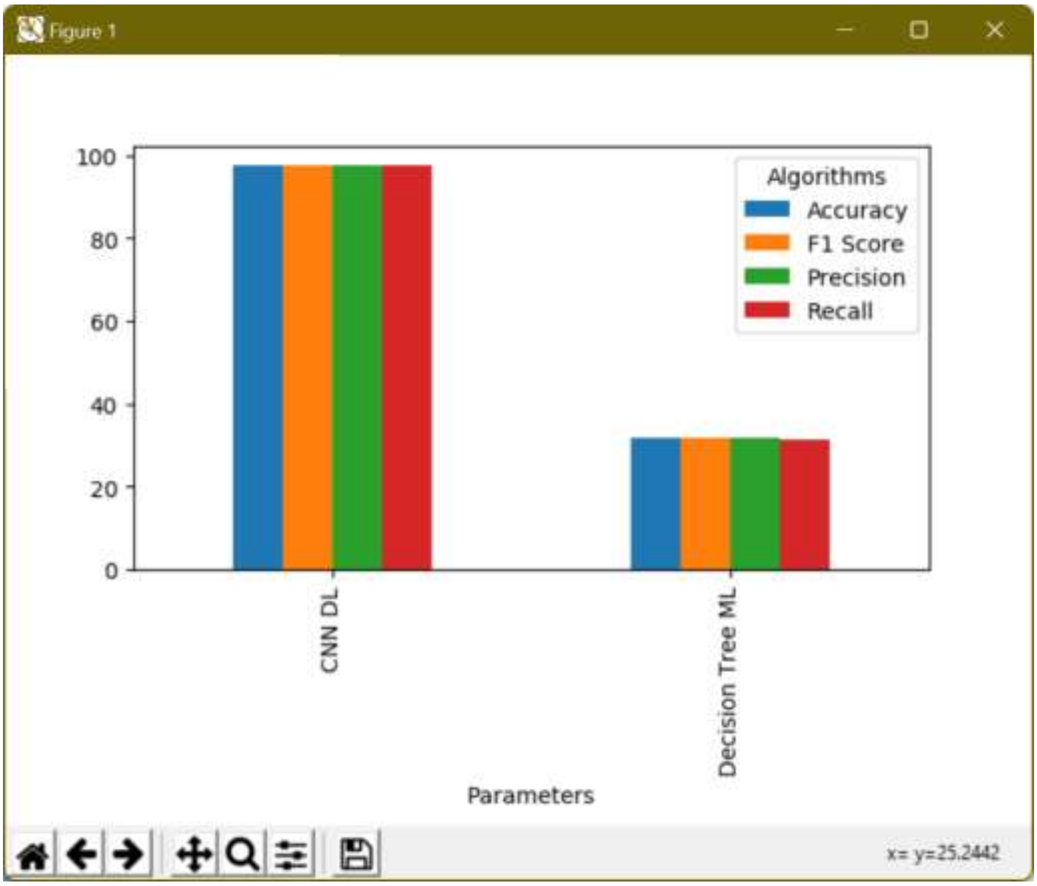

In above graph x-axis represents algorithm names and y-axis represents accuracy and other metrics in different colour bars.

6. CONCLUSION AND FUTURE WORK

This work implemented the detection of subtype blood cells using the advancement of neural networks known as deep learning CNN. Compared to machine learning algorithms, which use hand-crafted features as inputs, CNNs typically take raw images as inputs and learn hierarchical feature representations in an end-to-end fashion. By using CNN, we got 97% accuracy. The future work on the proposed word that we can compare the cropped with segmented WBCs images with different input sizes to find which is the best input type (cropped or segmented) and size that can provide more accurate classification of WBCs.

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