Demystifying Computational Techniques Used to Diagnose Tuberculosis

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Abstract. Tuberculosis is one of the most deathful diseases in the entire world and remains a major reason for death worldwide. In 2017, around 10.0 million people infected with tuberculosis. For detecting disease in the medical field using the computational technique, MRCNN & UNET Model has achieved impressive accuracy across multiple datasets like brain tumor (Multimodal Brain Tumor Image Segmentation (BRATS 2015) datasets), glaucoma and other based on data collected. This Research is based on the detection of WBC (White Blood Cell) form the stained Microscopy image, by collecting past data form patients. In India, medical patient data is not stored anywhere systematically, we made extra effort to find hidden patterns from data. The article deeply discusses the various approaches to diagnose tuberculosis. It summarizes the advantages and disadvantages of the existing techniques and why deep learning technology use in the various medical diagnosis process. In this study, we propose a fully automatic method for WBC segmentation, which is developed using MRCNN based deep convolutional networks. Proposed technique was evaluated on a dataset that contains 2500 stained microscopy images are used to train the system and 540 images are used to test the system. We have achieved nearly 92% accuracy with a low false-positive type error.

Keywords: Tuberculosis · UNET · Mycobacterium · Deep learning · Medical · Microscopy images · MRCNN

1 Introduction

Tuberculosis is caused by mycobacterium bacteria. The world health organization published a tuberculosis report every year. Diagnosis of tuberculosis is done in various ways like staining technique, X-Ray and etc. and its purpose is to provide information about diagnosis technique and Tuberculosis epidemic.

1.1 Tuberculosis

Tuberculosis is a deathful disease which is caused by mycobacterium bacteria [1]. Tuberculosis mostly damages the lungs but can also damage other parts of the body like eyes,

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brain & lags. According to the study of human skeletons, human affected by this diseases from thousands of years and this disease is remained unknown until Dr. Robert Koch discovered the Tuberculosis bacteria called mycobacterium [2]. Tuberculosis is of two types 1) Latent 2) Active. Most of the infections do not have any symptoms called latent tuberculosis. About 10% of latent tuberculosis is called active tuberculosis. Tuberculosis diseases are spread through the air from one person to another. Active tuberculosis is visible more in people who smoke and who affected by HIV/AIDS [3]. Classical symptoms are fever, cough with blood-containing mucus, Chest pain, weight loss, Chills and etc. [4, 5]. World health organization (WHO) publishing a report on tuberculosis since 1997 and its purpose is to provide information about the diagnosis technique and Tuberculosis epidemic. In 2017 report WHO discusses that 10.0 million cases of Tuberculosis registered worldwide and from that 1.3 million people deaths [6].

Mycobacterium is a family of Mycobacteriaceae [7]. Tuberculosis is caused by bacteria called mycobacterium bacteria. The size of mycobacterium is 2 to 4 μm in length and 0.2 to 0.5 μm in width [8]. Mycobacterium growing in road shape. Mycobacterium takes 15 to 20 h to spreading [9, 10]. Figure 1 and 2 show how the mycobacterium visible in different technique.

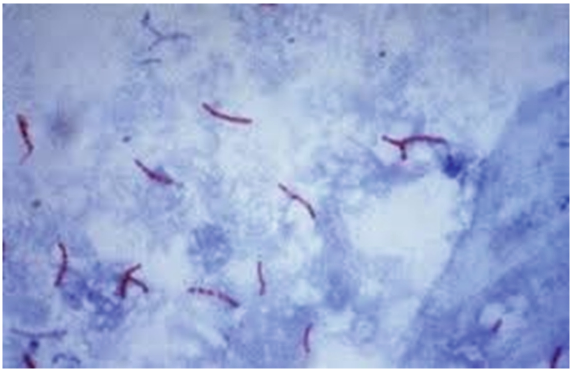

Fig. 1. Tuberculosis bactria in ZN staining technique [11] (Color figure online)

1.2 Diagnosis Techniques

Microscopy technique is the technical field of microscopes, its way to identify bacteria with the help of a microscope by staining them using gram stain [13]. Gram stain is a technique to classify the bacteria into two class gram-positive type and gram-negative type [14]. A microscopy image is a technique to view the microscopy world [15]. We have prepared the dataset by collecting the stained microscopy images, the system is trained using a prepared dataset and this system will help to diagnosis the various diseases having microscopic analysis based on images.

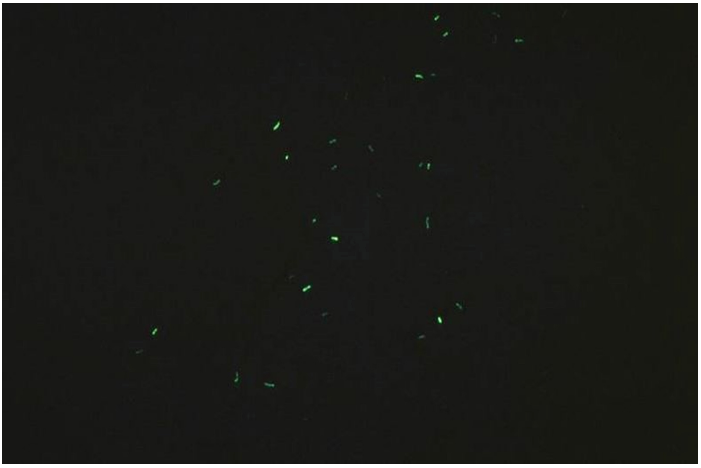

Fig. 2. Tuberculosis bactria in fluorescent staining technique [12] (Color figure online)

Tuberculosis diagnosis is done in a various way:

1. **Staining Technique**

The staining technique is the oldest technique and one of the most popular. This technique is cost-effective (Only RS. 300) but it is time-consuming because the result of the diagnosis process takes more than 4 h.

Type of Staining:

A. ZN Staining: In this technique background is visible in blue color and the object is visible in pink color. Figure 1 shows mycobacterium in this technique.
B. Fluorescent Staining: In this technique background is visible in black color and the object is visible in golden color. Figure 2 shows mycobacterium in this technique.

Staining Process:

Figure 3 shows the fluorescent staining process, it is a process of diagnosis of tuberculosis by the sputum Checking. For this process, two samples of sputum are collected and prepare the 2×3 slide and for diagnosis of tuberculosis, it needs to count mycobacterium bacteria. Size of mycobacterium is too small so for counting them zooming is perform (10×10 zoom so it is a matrix of 100 fields and at a time only one field is visible).

2. **X-Ray**

X-Ray technique is the process of diagnosis tuberculosis by checking the lungs. And it is a process of finding the whole in the lungs. Figure 4 shows the lung's image. Usual X-Ray based tuberculosis detection is done by an expert in the field of medical science by looking at x-Ray reports.

Fig. 3. Staining process

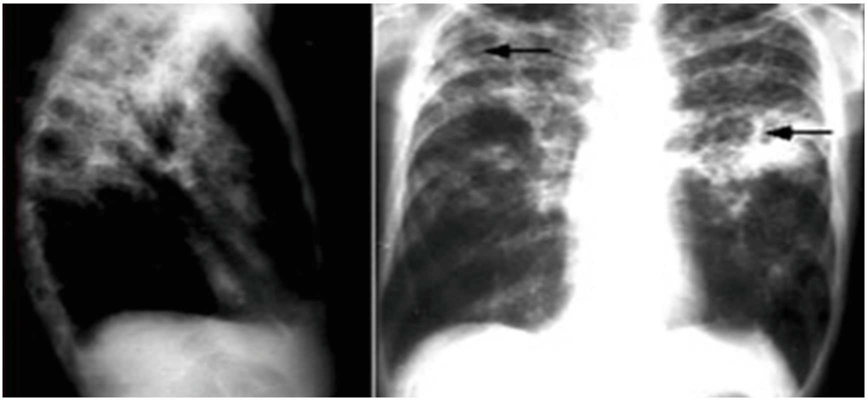

Fig. 4. Lung's X-Ray image [16]

3. **GeneXpert Machine**

GeneXpert Machine technique is a process of diagnosis tuberculosis by sputum checking. For this process, four samples of sputum are collected and directly put the sample into a machine and the final printed result is product. This technique is costly (US $17) but time saving. This process is based on the cartridge and the lifetime of a cartridge is only 18 months which is too short. The entire process is shown in Fig. 5.

1.3 Why Deep Learning

The previous topic describes information about different tuberculosis diagnosis techniques like staining, X-ray and GeneXpert Machine. A staining technique is a complex diagnosis process and the result of the process is dependences on the technical person who carried out the diagnosis process and also a technical person can also suffer from the eye problem due to the manual counting of this tine mycobacterium. A GeneXpert Machine and X-Ray techniques are costly and due to its cost, this technique is not prescribed by a doctor every time.

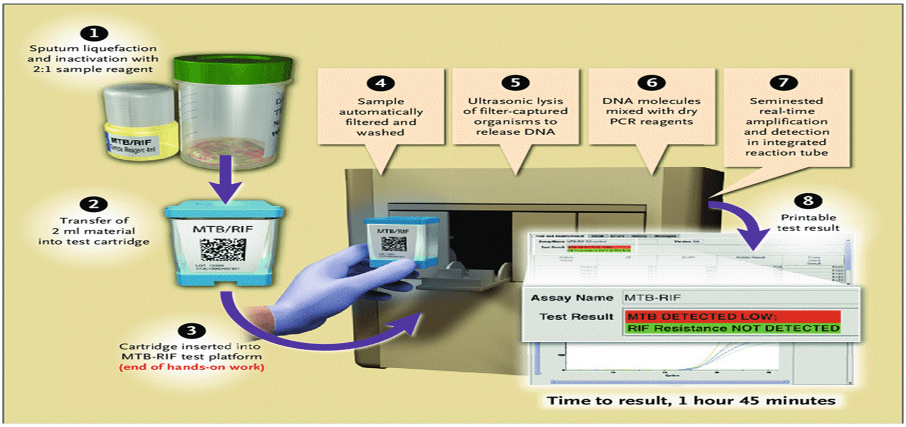

Fig. 5. GeneXpert machine [17]

There will be an error in the existing technology that is

1 False_positive type – means that Tuberculosis affected by a person but the report says that Tuberculosis is not affected. This means a normal report.
2 False_negative type – means that Tuberculosis not affected by a person but the report says that Tuberculosis is affected. This means a major report.

The Solution of the above address problem is given by the deep learning Technique (MRCNN, UNET model) used to diagnosis the process. In this diagnosis process human intervention is not there so there is no chicness of errors.

1.4 MRCNN

Masked Region-Based Convolution Neural Network (MRCNN) is an Image segmentation technique that is a combination of Faster RNCC and Fully Convolution Neural Network. Figure 6 Shown the MRCNN Architecture and it does the following steps.

1. It takes an image as input and extracts features from an image using ResNet 101 architecture.
2. The feature is passed to Region proposal network (RPM) which is used to predict that the object is present in given region?
3. With the help of ROI Align property of MRCNN, it finds out labels and bounding boxes of the fully connected networks.
4. All-Region IoU is calculated [IoU = Area of the intersection/Area of the union].
5. Output pass to convolution layer for pixel-wise Segmentation Mask.

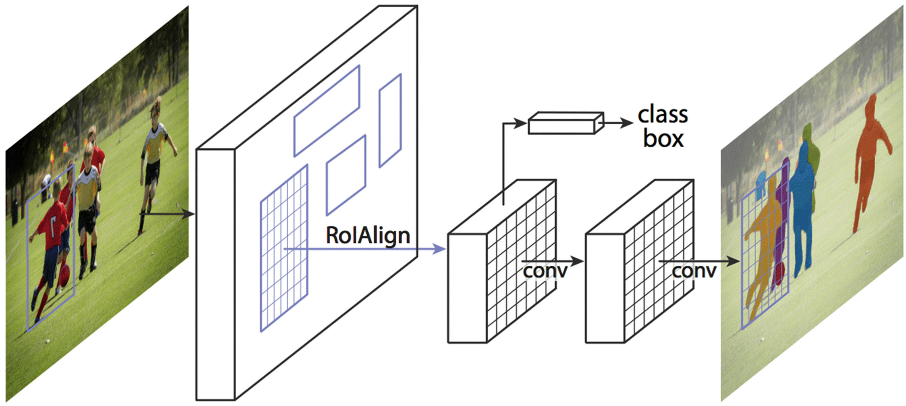

Fig. 6. MRCNN architecture [18]

1.5 UNET Model

UNET module is one of the most popular deep learning technique developed by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in 2015. UNET model is based on convolution neural network and its special developed for biomedical image processing. UNET model is also called as a 'U-shape' Architecture. Architecture is combination of Down-Sampling part and Up-Sampling part. The down-sampling part aim is to collect the information and the Up-Sampling part aim is to expanding path and provide a precise location [19].

2 Existing Research in Diagnosis of Tuberculosis and Medical Diagnosis

Tuberculosis is caused by mycobacterium bacteria. The manual process of diagnosis of tuberculosis (Staining Technique, X-ray, GeneXept Machine) some are complex and time-consuming and some are costly, so for giving the solution of existing manual process data mining, deep learning is used.

2.1 Tuberculosis

Mosin I. Hasan et al. (2011) discussed that tuberculosis is an infectious disease in India. The main objective is to develop the technique which categorizes tuberculosis in two categories as yes and no using naïve Bayesian classification and its aim is to extract the hidden patterns of Tuberculosis from the past patient data. Dataset contains detail of 154 cases by considering the 19 symptoms. 154 cases of tuberculosis is consider for processing by dividing the cases into two equal part of training and testing. The result is given in two ways using the weka tool and c program [20]. The advantages and limitations are discussed in the research finding section.

Yu Cao et al. (2016) discussed that tuberculosis is a deathful disease worldwide. The main aim of this research is to create large scale, real-world and freely available datasets of chest images and also provide well annotation and create a mobile phone based computing system to diagnosis tuberculosis effectively. Dataset is a collection of 4701 images from that 453 is normal images and 4248 abnormal images. The system is the train in two way Binary classification and multiple classification based level of infection [21]. Advantages and limitations are discussed in the research finding section.

Paras Lakhani et al. (2017) discussed that tuberculosis is danger disease worldwide. The main objective of this research is to show that how deep convolution neural network (DCNN) is used to diagnose tuberculosis is there or not. Dataset is a collection of cheat images of 150 cases and getting the accuracy of 97.3%. The author used two most popular DCNNs techniques called AlexNet and GoogLeNet for the diagnosis of tuberculosis. Process identify the hole in the chest [22].

2.2 Microscopy

John A. Quinn et al. (2016) discussed that microscopy is the standard method for diagnosing various diseases. Microscopy is one of the well adapted to low-resource, high disease burden areas. Microscopy based technique result of the process is dependent on the Technical person who carried out the diagnosis process. The main aim of this research is to show how microscopy is giving the best result for tuberculosis, malaria and Intestinal parasites. For the tuberculosis diagnosis process, stained sputum microscopy images are taken and using the CNN algorithm to train the system and find the mycobacterium and getting 0.99 area under the cove. For the malaria diagnosis process, stained blood sample microscopy images are taken and using the CNN system are train and find thick blood cell and getting 1.00 area under the cove [23].

Sonaal Kant et al. (2018) discussed that tuberculosis is danger disease worldwide. The author used deep learning techniques to diagnosis tuberculosis using CNN and SVM techniques. Accuracy is calculated using precision and recall factor and getting 83.78% and 67.55% respectively. The author used Dataset 3 of ZiehlNeelsen Sputum smear Microscopy image Database (ZNSM-iDB) which contain 6 set and each set have 50 field sputum images [24].

2.3 Medical Imaging Computation

Medical Image computation is done in many ways like data mining, image processing, and etc. one of the most popular fields for doing the processing of medical images called Deep learning (UNET). UNET model of deep learning is specially developed for biomedical image segmentation. The concept is introduced by Olaf Ronneberger, Thomas Brox, and Philipp Fischer in 2015 at the University of Freiburg, Germany. Figure 7 shows the architecture of the UNET model. Overall architecture UNET model has divided into two parts 1) Down Sampling and 2) Up Sampling.

UNET model is based on a convolution neural network. Architecture is work from left to right. Downsampling part is a collection of five convolution block and each block contains another three convolutions at the end of each convolution block max-pooling operation is performed. Upsampling part is a collection of four convolution block and

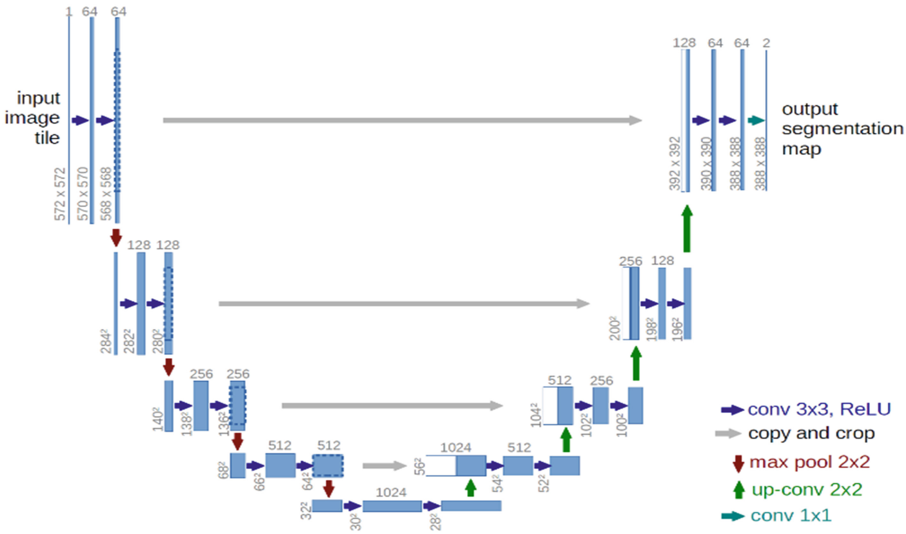

Fig. 7. UNET model architecture [19]

each block contains another three convolution blocks, the main purpose of Upsampling is to extract the content. The main purpose of downsampling is to capture context. The last step is the 1×1 convolution for classification of facture map into two class foregrounds and background [19].

Dong Hao et al. (2017) discussed that Detecting Brain Tumor Using MIR Technique is a very time-consuming process and the performance of the system is depended on the technical person who does this test, so automatic fully convolution network is used for efficient tumor segmentation based on UNET module of deep learning. For this technique multimodal brain tumor image segmentation BRATS dataset is used, the dataset has 220 high-grade brain tumor images and 54 low-grade brain tumor images. The primary effect of Brain Tumor is a dreadful type of cancer [25].

Artem Sevastopolsky et al. (2017) discussed that Glaucoma is a condition of eyes. A person can blind also due to this condition, so it is important to detect it in the early stages. One of the main symptoms of Glaucoma disease is a cup-to-disc ratio (CDR) is a ratio between heights of cup and disc. People are affected by Glaucoma or not, this decision is based on CIDR Parameter. CDR is at least 0.65 is considered Glaucoma positive [26].

Zhou Zongwei et al. (2018) discussed that UNet++ model is a more powerful architecture for medical image segmentation. The architecture of UNET++ is combination of encoder and decoder, this encoder and decoder are known as sub-network, this sub-network are combination of nested dense skip layers path called pathways. The main aim of using pathways is to reduce the semantic gap between encoding network and decoding network. Using this concept of path getting 92.52% of accuracy for detecting cell nuclei. UNet++ architecture is combination of nested and dense skip connection which is used to find fine-grained details of an object. In UNET model the feature maps of the encoder are directly expected in the decoder; however, in UNet++ model the feature maps of the encoder sub network first passed to the dense convolution level and then feature maps passed to the decoder [27].

Weng Yu et al. (2019) discussed that NAS (Neural Architecture Search) is a subtopic of auto-machine learning that has significant overlap on two parameter 1) hyper parameter optimization and 2) meta-learning. Current research on Neural Architecture Search based on three topics: search strategy, search space and different performance estimation strategy. Search space give the information about which architecture represented in given principle. The combine architecture of NSA and UNET is based on DownSC and UpSC, this DownSC and UpSC is called cell architecture. With the help of combine technique 98% of accuracy is obtain [28].

Zyuzin Vasily et al. (2018) discussed that modern cardiology of heart is done using ultrasound technique also known as echocardiography (EchoCG). Manual technique of cardiology is time consuming process and result is depends on technical person, so author used to train the system using UNET model. Health of heart is check by segmenting left ventricular (LV) border of the EchoCG. This LV image are represent in 2D manner, for training system 94 patients data is used and using this proposed technique author obtain 92% of accuracy [29].

3 Research Findings

Mosin I. Hasan et al. [20] discussed that the manual tuberculosis test process is complex and the result is dependent on the technical person. Using a naïve Bayesian algorithm author achieved 78% accuracy. Dataset content only 154 cases and its symptoms. The efficiency of naïve Bayesian by selecting weighted features. Dataset is of very small size and the author has not discussed False-negative results as in disease diagnosis false negative has a crucial impact on the efficiency of the algorithm. This technique can be used as a supplementary method to further strengthen the result of other systems. Apart from this more data should be collected [20].

Yu Cao et al. [21] discussed that successfully creating a well-formed tuberculosis chest dataset that contains 4701 images from that 453 is normal (tuberculosis not there) and 4248 abnormal (tuberculosis is there). The system is trained in two-way Binary classification and multiple classifications based levels of infection and getting 89.6% and 62% accuracy respectively. But in the binary case, it only saying that tuberculosis is there or not by only find the whole chest images form that we are not getting any information about at which stage tuberculosis is there. In the second case multiple classifications not discuss anything about the false negative, it means that the tuberculosis is caused by the person but report saying that it not there so it's a very compacted thing [21].

Paras Lakhani et al. [22] discussed that using DCNNs techniques (AlexNet & GoogLeNet) system is trained using 150 cases of tuberculosis and getting 97.3% accuracy. The ratio of misclassification is more in case of new dataset [22].

Dong Hao et al. [25] discussed that in the UNET model Soft Dice based loss function is used for making unbalanced samples uniformed. Data Augmentation technique is used to increase the number of training samples. Data augmentation methods like flipping, rotation, shift, and zoom. The limitation of this proposed method is system is evaluated using cross-validation schema using this proposed technique, getting 82% accuracy and provides an unbalance predicate [25].

Artem Sevastopolsky et al. [27] discussed that manual method of optic disc and cup requires about eight minutes per eye for technical person and this test done efficiently using UNET in less time. The author used less number of the filter then the original UNET Module have, the main aim of the author is to provide lightweight architecture and getting 89% of accuracy [26].

Each and every method have its own pros and cons. Existing work done in tuberculosis will diagnosis diseases correctly but the system is trained on a dataset that contains small sample and also that samples are not of all the type. Accuracy getting in existing system is also too less. Existing research work not force on false-negative type of prediction, false-negative means tuberculosis is caused by the person but system product result as tuberculosis is not there which major problem is. Research work done in 2017 on the chest dataset consider only 13 cases to train the system which not the correct way for diagnosis the diseases.

4 Implementation Result

In this study, we developed MRCNN model to detect and return mask of WBC cell in an image. System is train on 2500 images of WBC and 540 image are used to test the system. Using this MRCNN we get 92% of accuracy. The system take original image and its annotation file as an input at time of training. The system take original image and product output as an image which contain highlight mask of all the WBC.

Figure 9, 10, 11 and 12 show the result of Object segmentation in which it display the WBC cell mask if image have more than one WBC cell then it display in different color.

Steps to Implement Mask RCNN for Identifying WBC Cell

1. To train the system using MRCNN model annotation of an image is required to identify WBC cell. Annotation is done using VGG Image Annotation tool, Fig. 8 shows the example of Image Annotation.
2. For the implementation of MRCNN Required following Packages are need to be install which is opencv-python, numpy, keras $\geq$ 2.0.8, matplotlib, cython, scikit-image, tensorflow $\geq$ 1.3.0, h5py, imaguag, IPython, scipy, and pillow.
3. Download pre-trained weight of a COCO model called mask_rcnn_coco.h5.
4. For doing a Predicting on our image we will use the Mask R-CNN architecture and the pre-trained weights of COCO model to generate Mask of WBC cell.

Fig. 8. VGG image annotator example [30]

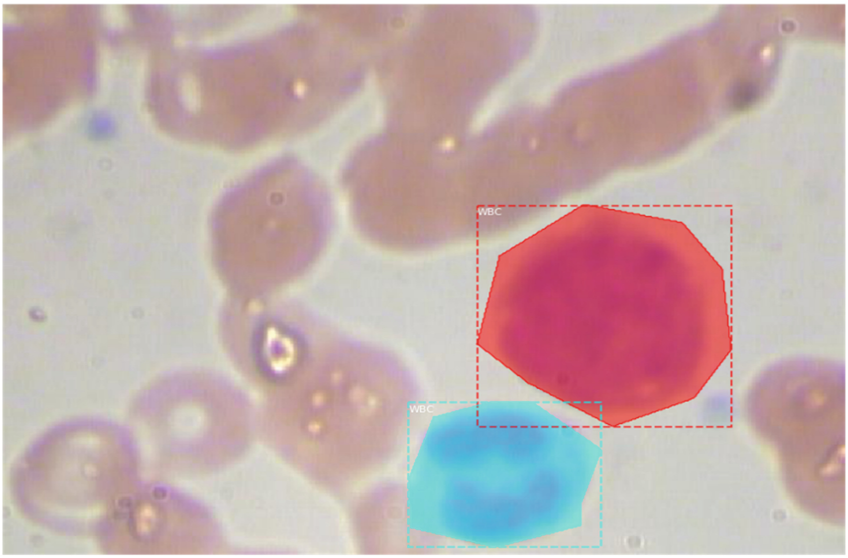

Fig. 9. WBC object mask output—1

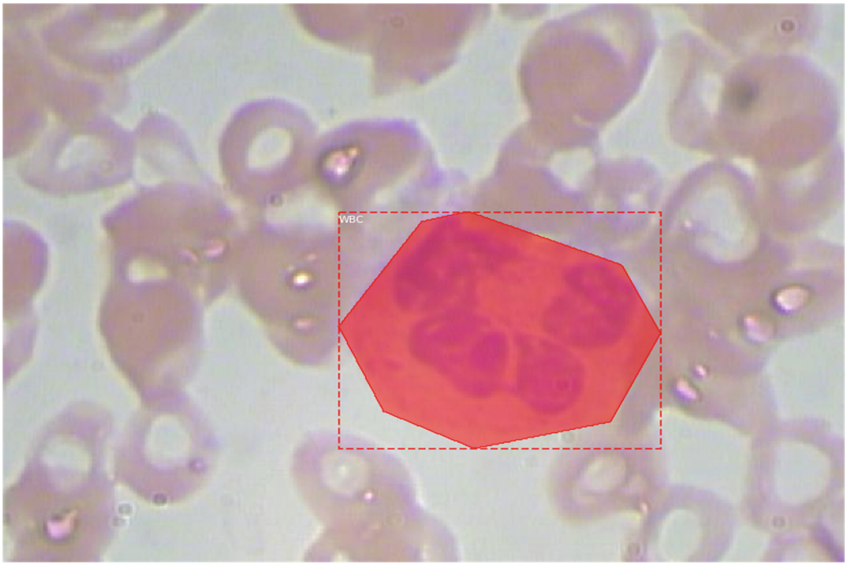

Fig. 10. WBC object mask output—2

Fig. 11. WBC object mask output—3

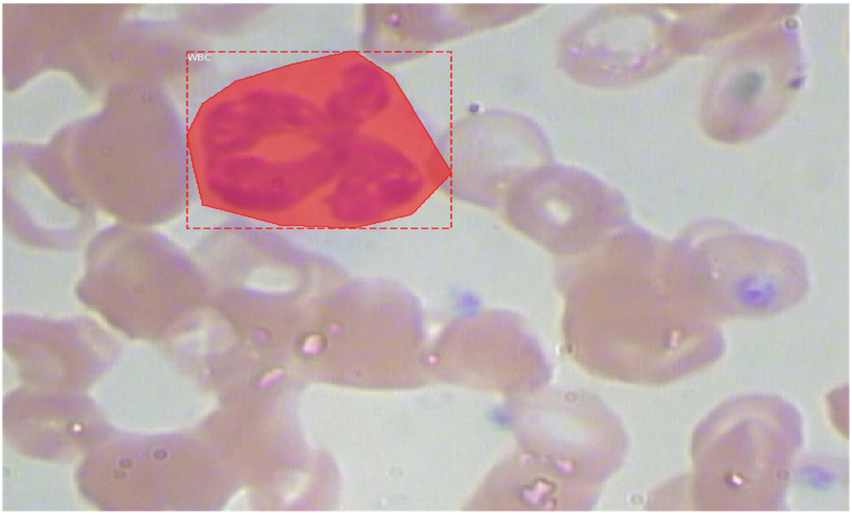

Fig. 12. WBC object mask output—4

5 Conclusion

Accounting to the world health organization tuberculosis is one of the deathful diseases worldwide. One fourth of the world population affected by tuberculosis. In 2017 10.0 million cases of tuberculosis are resisted worldwide and from that 1.3 million people deaths. Well-formed and annotated Dataset pertaining to stained slides is not available which important task is and it needs attention. X-Ray based diagnosis technique has potential but the cost of X-Ray based technique is high and the result is based on the technical person who carried out the diagnosis process and due to cost concern it is prescribe in later stage. Staining based technique for diagnosis of tuberculosis sputum checking is done by finding the mycobacterium. Size of mycobacterium is tony (0.2–0.5 μm) and manually counting of the bacteria is a complex task which is prone to error due to manual intervention of technical person., we come known that how the MRCNN model give the efficient result in medical diagnosis like brain tumor detection, Glaucoma detection and etc. MRCNN model has capability to detected tony thing and give the best result. Well-formed and well-annotated dataset (that contain sputum stained images) is not available. Furthermore, Creation of this dataset the having sputum stained images are the imported task to explored it further. UNET model is special developed for biomedical image processing. We also combine MRCNN and UNET Model to increase accuracy of diagnosis process.

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