Abstract

Keywords: Automatic Detection, Microscopic Image, Parasite Egg, Fecal Sample, Segmentation, classification, Identification, Image processing, Feature extraction, Machine Learning, Deep Learning, Convolutional Neural Network, Semantic Segmentation, Object Detection

The automatic detection and identification of parasite eggs in microscopic images of fecal samples involve finding and classifying various types of parasite eggs using computer vision techniques. However, developing an effective automatic system for the identification of numerous types of parasite eggs poses several challenges. These challenges include the lack of standard datasets, the presence of debris in images, the similarity of parasite eggs in size, shape, and texture, overlapping structures, varying image backgrounds and illumination effects. Despite extensive research and various proposed methods, current techniques often perform poorly in practical conditions due to the presence of non-egg structures and debris that resemble parasite eggs. This thesis explores various methods for the automatic detection and identification of parasite eggs in microscopic images and proposes optimal approaches for the segmentation, feature extraction, and classification of different types of parasite eggs in microscopic images of fecal samples.

Developing an automatic system for the detection of parasite eggs involves several stages: preparing an image dataset, pre-processing the images, segmenting the images to detect objects, extracting features, and classification. This research begins with creating a dataset of microscopic images of fecal samples containing three species of parasite eggs: Roundworm (Ascaris lumbricoides), Hookworm (Ancylostoma duodenale/Necator americanus), and Whipworm (Trichuris trichiura). Various data augmentation techniques are employed to increase the number of images, ensuring that different image processing and machine learning methods can be effectively validated in later stages. Ground truth masks are also prepared by annotating parasite eggs and various non-egg objects with similar properties to validate the deep learning-based segmentation and object detection models.

Various experimental analyses are conducted using different image segmenta-

tion methods, including thresholding, edge detection, clustering-based algorithms, watershed algorithms, and the Circular Hough Transform (CHT). Based on the analysis and after numerous trials and errors, an optimal segmentation approach is proposed that utilizes Canny edge detection and the Circular Hough Transform method. The approach also includes several image pre-processing operations, such as brightness and contrast enhancement and edge sharpening. To eliminate redundant detections of the same object and enhance segmentation quality, several post-processing operations are employed, including morphological operations and Non-Maximum Suppression (NMS). The approach is evaluated on the images of our own dataset and shows satisfactory results, despite the heavy load of debris in the images.

Six different feature sets are extracted from the segmented objects. These feature sets include Hu's seven invariant moments, Legendre moments, Chebyshev moments, Krawtchouk moments, texture and shape-based features, and pixel intensity-based features. The effectiveness of the feature sets is evaluated using different classification algorithms, including ANN, SVM, kNN, Decision Tree, Random Forest, and XGBoost. Extensive analysis is performed on the results to determine the most optimal feature set and classification algorithm. The shape- and texture-based feature set is found to perform best in classification, achieving an average accuracy of over 98%. Additionally, the performance of the classifiers in identifying parasite eggs is assessed by categorizing non-egg objects into multiple classes. In this approach, the three parasite egg classes achieve the highest classification accuracies of 98.92%, 98.39%, and 99.29%, respectively. The analysis shows that while overall classification accuracy decreases when using multiple non-egg classes, the identification rate of parasite eggs improves. Experimental findings suggest that texture-shape-based and pixel intensity-based features outperform image moment-based features.

Finally, this research presents the application and effectiveness of deep learning-based approaches for the segmentation, classification, and detection of parasite eggs in microscopic images. The well-known semantic segmentation architecture UNet is utilized and analyzed with various parameter tuning and configurations for both binary and multi-class classification problems. Using the U-Net model with ResNet50 as the backbone in binary classification mode, the study achieved an IoU of 7.2, precision of 92.31%, and recall of 89.27% through transfer learning. In multi-class mode, with three parasite egg classes and one non-egg class, and VGG19 as the backbone, the best results were an IoU of 6.7, precision of 87.47%, and recall of 86.16%. A CNN-based model is proposed for classifying the segmented objects, achieving over 99% training and 98% of accuracy. Additionally, the popular object detection framework Faster R-CNN is employed with transfer learning and parameter tuning to detect various types of parasite eggs, achieving a satisfactory mAP of 0.88.

The analysis shows that deep learning-based classification and object detection approaches can be more suitable than traditional machine learning approaches in this field, provided there is a sufficient amount of data. However, it is observed that the semantic segmentation approach is only effective when applied as multi-class segmentation, which requires a large amount of accurately annotated data and significant computational power. While binary segmentation is simpler, more time-efficient, and more accurate than multi-class segmentation, using it in conjunction with a separate classification approach can increase the complexity of the entire system for automatic detection and identification of parasite eggs. Further experimentation and analysis of different approaches developed for addressing issues of automatic detection and identification of parasite eggs in microscopic images of fecal samples can be explored in subsequent research.

In this thesis, the automatic detection and identification of parasite eggs in noisy microscopic images is addressed to target the critical challenges such as overlapping structures and the presence of debris. Using advanced image processing, machine learning and deep learning techniques, this research work achieved high detection accuracy, with metrics such as mAP, IoU, precision, recall, F1 score for the identification of three parasite species and discriminating them from other non-egg objects.

Beyond these technical outcomes, this research demonstrates significant potential in real-world medical diagnostics. By automating parasite identification, our approach supports more rapid and accurate diagnosis, reducing the burden on laboratory personnel and enabling faster patient treatment. By leveraging machine learning and deep learning techniques, this work thus contributes to improved diagnostic workflows and has substantial implications for clinical and epidemiological applications.