Chapter 8

Conclusion and Future Direction

8.1 Conclusion

This doctoral thesis reports a work pursued to achieve the goal of improving the automatic detection and identification of various types of parasite eggs in microscopic images of fecal samples of pigs using computer vision techniques. The thesis is organized into eight chapters, each detailing the different approaches employed during our research.

In Chapter 1, the significance of computer vision techniques in parasite egg analysis and their importance in medical diagnostics is discussed. The advancements in computer vision techniques and the way they have revolutionized the field, allowing researchers and healthcare professionals to automate and enhance the process of detecting and identifying parasite eggs in medical images are discussed in this chapter.

In Chapter 2, an extensive review of existing literature on the automatic detection and identification of parasite eggs in microscopic images is reported. The review highlights the strengths and weaknesses of different research approaches and identifies areas for improvement. This served as the basis for our research by identifying goals and objectives, challenges and opportunities, and guiding the decisions on methodologies for image segmentation, feature extraction, classification, and object detection.

Chapter 3 lays the groundwork for a comprehensive study into the segmentation and classification of parasite eggs. At the beginning, the chapter describes the process of creating a dataset comprising microscopic images of three types of parasite eggs: Roundworm, Hookworm, and whipworm, that are collected from two different sources. The dataset laid the basis for subsequent analysis, enabling the application of image segmentation and object detection approaches. To apply deep learning-based segmentation and object detection techniques, the number of images in the original dataset is increased using various data augmentation methods. The images are then annotated to generate ground-truth labels indicating the parasite eggs and non-egg objects. Following the image segmentation process, a dataset containing segmented images of parasite eggs and non-egg objects for the classification tasks is prepared.

In Chapter 4, an image segmentation approach is designed for the parasite egg images in our dataset is proposed. This approach integrates various traditional image processing and segmentation techniques. Initially, several image segmentation methods, including binary thresholding, edge detection, watershed algorithms, and machine learning-based k-means clustering methods, are evaluated. Based on the evaluation results, the Canny Edge detection method is selected. Following edge detection, Circular Hough Transform (CHT) is employed to improve detection of circular and elliptical-shaped objects, addressing challenges posed by sample debris in the images that complicate segmentation. The issue of multiple detection of the same object by the CHT is addressed by applying a non-maximum suppression method. Finally, the detected objects are automatically extracted from the original RGB image using bounding box coordinates from the binary segmented image.

Chapter 5 describes the steps involved in extracting various types of features from segmented or detected objects. Six sets of features are selected and extracted for classifying the detected objects. This includes four types of image moments: Hu moments, Chebyshev moments, Krawtchuk moments, and Legendre moments. Additionally, several texture-based features are extracted based on the methodology described in [29,127]. These texture features are combined with simple shape-based descriptors such as area, perimeter, aspect ratio, and circularity to form a more effective feature vector. The sixth feature set is created by utilizing pixel intensity-based measures such as mean, maximum, and minimum intensity, variance, and standard deviation. A block-based approach is employed where the object's image is divided into uniformly-sized blocks to extract intensity values from each block. The final feature vector is formed by combining values from all blocks.

Chapter 6 explores various machine learning-based classification algorithms for identifying parasite eggs using the feature sets mentioned in Chapter

5. Algorithms such as ANN, SVM, kNN, decision tree, random forest, and XGBoost are employed with hyper-parameter tuning for performance optimization. It is observed that SVM and XGBoost outperform other classifiers in accurately identifying parasite eggs and distinguishing them from non-egg objects. The most effective feature sets include texture, shape-based descriptors, and pixel intensity-based measures. These findings underscore the critical role of classifier selection and feature representation in achieving optimal parasite egg identification rates. Importantly, categorizing non-egg objects into multiple distinct classes, typically 2 or 3, significantly improves the classification rates of parasite eggs. This highlights the importance of categorizing non-egg objects before training classifiers to enhance accuracy and reduce misclassification rates.

Chapter 7 describes the use of Convolutional Neural Networks (CNNs)-based approaches for the segmentation, detection, and classification of parasite eggs in microscopic images. A semantic segmentation model, UNet, is employed for the segmentation of parasite egg images. By adopting transfer learning techniques, this work aims to improve the segmentation results for both single-class and multi-class scenarios. The next step involves classifying segmented objects using Convolutional Neural Networks (CNNs)-based models. Two approaches are employed: transfer learning and training a custom CNN model from scratch. Both approaches achieve remarkable classification accuracy, nearly 99%. Additionally, state-of-the-art CNN-based object detection methods for detecting parasite eggs are explored. The Faster R-CNN model is fine-tuned with optimized hyper-parameters, using backbone networks like VGG16, VGG19, and ResNet50 to enhance the accuracy of parasite egg detection. The work achieves the highest mean Average Precision (mAP) of 0.88, which is satisfactory given the limited amount of data available.

Finally, Chapter 8 concludes the thesis by summarizing the results and methodologies adopted in our research work. Our research indicates that deep learning-based approaches excel over traditional image processing and machine learning methods in accurately detecting and identifying parasite eggs in microscopic images. However, it is essential to note that these models require extensive and diverse datasets, as well as substantial computational power, to achieve optimal performance. This insight suggests opportunities for future research to further refine and enhance these techniques for practical implementation in medical diagnostics.

In summary, the key contributions of this thesis to overcome the challenges related to the automatic detection and identification of parasite eggs in microscopic images are as follows:

- A database of three different types of parasite egg images is developed with annotations for segmentation, classification, and object detection. Data augmentation techniques such as shifting, rotating, flipping, and blurring are applied to artificially increase the dataset size and mitigate the class imbalance problem.

- An effective approach for segmenting the parasite eggs is developed using a combination of traditional image segmentation techniques, including Canny Edge Detection, Circular Hough Transform (CHT), and Non-Maximum Suppression (NMS), even in the presence of debris and complex backgrounds. Additionally, methods to improve image quality, such as noise removal and normalization of illumination, are employed to enhance the reliability of the input images. Morphological operations are applied as post-processing techniques to refine the segmentation quality further.

- A wide range of features, including moment-based features (Legendre, Hu, Chebyshev, and Krawtchuk moments), texture-based descriptors, shape and size-based features, and pixel intensity-based measurements, are extracted to capture diverse morphological attributes. Extensive experimentation identifies robust feature combinations that handle morphological variability effectively.

- Machine learning classifiers such as ANN, SVM, kNN, Decision Tree, Random Forest, and XGBoost are trained on the extracted features to ensure accurate differentiation between species and within species despite overlapping morphological characteristics. These classifiers demonstrate high precision and recall, reducing misclassification rates. Moreover, the thesis proposes categorizing non-egg objects into multiple classes to enhance the identification accuracy of parasite eggs.

- Oversampling of minority classes is achieved using various data augmentation techniques, including blurring, zooming, translation, mirroring, flipping, and shifting. These methods effectively balance the dataset and improve the representation of under-represented classes, addressing the class imbalance issue.

- Deep learning models, including CNN-based classifiers, UNet, and Faster R-CNN, are utilized for classification, segmentation, and object detection. A proposed CNN architecture achieves over 98% test accuracy, effectively distinguishing parasite eggs from non-egg objects. UNet attains an IoU score of 0.72 with 92% precision and 89% recall, while Faster R-CNN achieves a mAP of 0.88, demonstrating robust performance in identifying and localizing multiple egg types.

This research has several practical applications, including integrating the model into clinical diagnostic systems to automate parasite egg detection and improve speed and accuracy. In remote areas, portable devices with this model could enable on-site testing without requiring advanced infrastructure. Additionally, the model can support public health surveillance by monitoring infections, tracking outbreaks, and aiding timely interventions. These applications demonstrate its potential to improve diagnostics in clinical, field, and public health settings.

8.2 Future Direction

Throughout our research journey on the automatic detection and identification of parasite eggs, microscopic images of fecal samples containing only three distinct types of parasite eggs are used. However, the methodologies and insights presented in this thesis can serve as pioneering work, with the potential to scale up and detect various other types of parasite eggs.

This research reveals several areas within this field that offer potential for exploration in future research endeavors. These areas include:

1. Dataset Expansion: Acquiring or generating a larger and more diverse collection of microscopic images of different types of parasite eggs in various environments will enhance the training of more robust and accurate detection and classification models. A future direction for this research involves collaborating with medical institutions to access a broader range of samples, including those from different species and geographic regions. This would not only enhance the diversity of the dataset but also ensure the model's robustness across various environmental and epidemiological contexts, making it more applicable in global diagnostic settings.
2. Identification of growth stages of parasite eggs: Analyzing various stages of growth in the life cycle of parasite eggs has the potential to enhance medical diagnostics and parasitology. It is crucial to capture images of parasite eggs at different stages of growth to develop automatic systems for this task.

3. Development of Efficient Deep Learning-based Techniques: Deep learning-based techniques are typically resource-intensive in terms of hardware, data, and time. There is a growing need to develop techniques, particularly for parasite egg detection and identification, that are more computationally efficient. This is a future direction and an active area where researchers can focus their efforts.

4. Detection of Parasite Eggs in Other Biological Samples: Future work will also include the use of additional samples, such as blood or tissue, to enhance the system's versatility. By adapting the model to detect and identify parasites in these different sample types, it could provide a broader application in diagnostics, offering a more comprehensive tool for detecting parasitic infections across various biological materials. This extension could involve addressing the unique challenges posed by different sample characteristics, such as varying image quality or the presence of additional contaminants, to ensure the system's accuracy and reliability across diverse diagnostic scenarios.

   The research on automatic detection and identification of parasite eggs of various types, sizes, and shapes in noisy microscopic images of fecal samples has significant potential for real-world applications in diagnostic systems. By integrating this model into existing microscope imaging software, laboratories and clinics could automate routine parasite detection, enabling technicians to focus on complex cases, thus improving efficiency and ensuring timely diagnoses. In resource-limited settings, this automation could make parasitic diagnostics more accessible and affordable, reducing the reliance on highly trained personnel and enabling broader public health initiatives. Portable diagnostic devices equipped with this model could also be deployed for field applications, supporting real-time diagnostics in remote and underserved areas. However, a key limitation is the high computational cost associated with training deep learning models, which can require powerful hardware resources not always available in smaller labs or clinics. To overcome this, model compression techniques, such as pruning and quantization, or lightweight architectures, could be employed to reduce model size without sacrificing significant accuracy. Additionally, transfer learning and pre-trained models can help reduce training demands, enabling the system to perform efficiently on standard computing resources while maintaining diagnostic accuracy and reliability. These strategies could make the model more feasible for deployment in practical settings, enhancing the accessibility and utility of automated parasite detection.

For future work, the research includes exploring the potential of deploying this model in real-time diagnostic settings, which could significantly enhance its practical value. Real-time processing would allow for immediate detection and identification of parasite eggs during microscopy, offering on-the-spot diagnostic feedback. This capability would be particularly valuable in high-demand clinical settings and field applications where quick decision-making is essential. Implementing real-time capabilities could involve optimizing the model's processing speed and reducing computational load through techniques like model compression, hardware acceleration with GPUs, or edge computing. Real-time adaptation would not only streamline diagnostics but also make automated parasite detection more effective in diverse environments, advancing its usability in both developed and resource-limited healthcare settings.