Editorial

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Artificial Intelligence in Hematopathology

Iffat Jamal

Associate Professor, Department of Hematology Pathology,
Indira Gandhi Institute of Medical Sciences, Patna 800024, Bihar, India.

INTRODUCTION

Digital pathology (DP) involves digitizing pathological slides using full slide scanners and analyzing these digitized whole section images. It employs Whole Slide Imaging (WSI) to capture numerous pathological images with high resolution histological features. While scanners typically produce 20× to 40× digital slices for tissue diagnosis rapidly, blood pathological smears necessitate higher magnification scans (60× or 100×) for precise pathological information, especially for peripheral blood or bone marrow (BM) smears.[1]

Histopathological image analysis algorithms, primarily based on artificial intelligence (AI), have emerged to extract valuable information from digitized images. These AI powered computer aided diagnosis methods offer hematopathologists a potent tool that can potentially surpass traditional microscopy in effectiveness.

AI is a field of computer science striving to replicate human like intelligence in machines. Lack of substantial datasets and computing power traditionally hindered AI development. Nonetheless, advancements in image technology and computing, particularly in Graphical Processing Units (GPUs), have led to the accumulation of vast image data and enhanced AI capabilities in various domains such as image processing, language recognition, and natural language processing.[2]

Commercially developed AI tools, including Lunit, Ibex, aetherAI, DeepBio, PathAI, Paige, have seen increased usage in solid tumor anatomical pathology. Some tools are also utilized in hematological diseases; for instance, Deep Flow, developed by Deep Analysis Intelligence, is the world's first flow cytometry AI cloud diagnosis system, achieving a diagnosis accuracy rate of up to 95% in acute leukemia, significantly faster than human doctors.[3]

Although AI is poised to benefit many clinical health science areas, this review focuses specifically on its application in digital hematopathology. It encompasses tasks like identifying normal hematopoietic cells, classifying diverse blood cells, morphologically identifying acute leukemia, and diagnosing clonal hematopoietic stem cell disorders. The review aims to offer insights into the potential applications of AI in these hematopathology areas.

This section seems to discuss the application of AI (Artificial Intelligence) in the field of hematology. It delves into machine learning, which is a subset of AI, focused on machines mimicking human intelligent behavior. Machine learning encompasses supervised, unsupervised, and reinforcement learning methods utilizing various techniques such as regression, support vector machines (SVM), decision trees, and neural networks.[4]

In medicine, machine learning finds application in three main categories: intelligent diagnosis and treatment, medical image recognition, and medical robots. Intelligent diagnosis involves leveraging AI for disease diagnosis and treatment by aiding doctors in analyzing pathology and examination reports through technologies like big data and in-depth mining. Medical image recognition involves AI assisting doctors in locating lesion areas in medical images, reducing missed diagnoses and misdiagnoses. Additionally, robots are employed in various medical aspects such as intelligent prosthetics, exoskeletons, and healthcare robots aiding medical staff.[4,5]

Deep learning, an emerging algorithm in machine learning, emphasizes simulating the human brain by using layered networks to analyze data relationships and features. Deep neural networks, comprising interconnected nodes across multiple layers, employ techniques like convolutional neural networks (CNN), recurrent neural networks (RNN), and Long Short-Term Memory (LSTM) for tasks like image classification and computer vision in medical imaging. These models have shown superior results in aiding diagnosis, risk stratification, and treatment planning in medical imaging. Moreover, with the rise of Whole Slide Imaging (WSI) generating large volumes of digitized slide images, deep learning models can efficiently learn to classify tissues and cells, benefitting from enhanced computer hardware performance, especially in GPU computing power.[5]

Moving to the identification of normal hematopoietic cells, accurate segmentation and identification of blood cells are crucial in diagnosing benign and malignant hematologic diseases. Manual counting of these cells in microscopic images is laborious and subjective, leading to the development of automatic hematopoietic cell classification technologies. Some studies have proposed iterative structured circle detection algorithms and employed deep CNNs for identifying white blood cells (WBCs) in blood smear images, achieving high accuracies around 95.3% to 98.4%. Others have utilized object detection approaches for leukocyte identification, using large datasets and achieving high overall accuracy of up to 96.1%.[6-8]

These advancements in AI and machine learning showcase potential in revolutionizing hematology by automating cell identification processes, aiding diagnosis, and leveraging technology for enhanced accuracy and efficiency in medical practices.[9]

Despite the advancements in machine learning, some cell populations are still analyzed manually using imaging flow cytometry, which can be costly and potentially confounding. To address this, Lippeveld *et al*. developed an automated and stain free method to classify white blood cell types using deep learning and classical machine learning approaches. Interestingly, they found that deep learning approaches did not consistently outperform methods based on manually engineered features.

Furthermore, there have been challenges with domain shift, where deep learning models trained on one dataset perform poorly when tested on another dataset. Recent work by Pandey *et al*. addressed this problem using unsupervised domain adaptation (UDA) techniques, improving performance when models were tested on data from different settings.

Additionally, recent studies have explored CNNs' ability not only to classify current cell types from images but also to predict future cell states based on past or current cell shapes. For instance, Buggenthin *et al*. developed a deep neural network that predicts lineage choice in primary hematopoietic progenitors using time-lapse microscopy images, linking brightfield and fluorescence microscopy. This innovative method efficiently identifies stem cell differentiation without the need for fluorescently labeled samples.

Platelet Function and Megakaryocytes

Blood disorders related to platelet function encompass a diverse range of conditions, often diagnosed by symptoms such as bruising, skin bleeding, or excessive bleeding post-injury or surgery. Objective and effective quantification and classification of megakaryocyte shapes can significantly enhance insights into platelet function defects. Identifying abnormal megakaryocytes is crucial in diagnosing disorders like Philadelphia negative myeloproliferative neoplasms (MPNs), where distinguishing between conditions like essential thrombocythemia (ET), polycythemia vera (PV), and primary myelofibrosis (PMF) can be challenging. Methods utilizing machine learning, such as a deep neural network named Single Shot Multibox Detector coupled with image segmentation techniques like U-Net, have achieved high accuracy in predicting megakaryocyte features in stained sections, aiding in diagnosing these blood diseases.[7]

Red Blood Cell Disorders

Morphological changes in red blood cells (RBCs) in diseases like sickle cell disease (SCD) reflect alterations at the protein level, influencing cell shape and size. Computational frameworks based on deep convolutional networks have been developed to efficiently classify heterogeneous shapes in sickle blood, achieving high recall rates. These studies demonstrate the potential of machine learning methods in obtaining objective descriptions of blood cell morphology.[8]

AI Applications in Leukemia

Leukemia, originating in the bone marrow, involves the overproduction of immature leukocytes. Morphological identification plays a crucial role in diagnosing acute myeloid leukemia (AML) and acute lymphoblastic leukemia (ALL). Various computational frameworks employing machine learning techniques like support vector machines (SVM) and deep convolutional neural networks (CNN) have shown promising results in classifying and detecting leukemia and its subtypes from microscopic blood images. These methods have exhibited high sensitivity, specificity, and accuracy, enhancing the diagnosis and classification of these diseases.[9]

Clonal Hematopoietic Stem Cell Disorders

Hematopoietic stem cell disorders, including myelodysplastic syndromes (MDS), can be diagnosed based on morphological manifestations. Automated diagnostic support systems, combining deep learning image recognition systems with decision making algorithms, have been developed to aid in diagnosing MDS by classifying blood cell types and morphological features with high sensitivity and specificity.[10]

CONCLUSION

AI technology enables high-through put morphological classification of blood cells, offering new possibilities for identifying and classifying heterogeneous cell populations involved in blood diseases. Challenges such as obtaining sufficient labeled images for training models and interpretability of AI output results exist. However, AI significantly promotes and standardizes the diagnostic process in hematopathology, complementing and assisting human activities in this field.

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