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NUCLEAR ABNORMALITIES RELATED MICROSCOPIC IMAGE SEGMENTATION: DEEP LEARNING APPROACH

Bioinformatics

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ABSTRACT

Objective: The present study aimed to develop and evaluate an automated microscopic image segmentation approach based on deep learning for accurate identification and delineation of cellular structures.**Methods:** A computational and image-analysis research was conducted by using microscopic image and their matching expert-generated segmentation annotations served as the foundation for this study design. The microscopic image of grayscale on nuclear abnormalities was selected. The segmentation of the input image was incorporated in Fiji-ImageJ tool of MS Window platform (version, 1.54n). After incorporation of image, plugin was selected for TWS (version-3.2.11) machine learning tool.**Results:** The threshold curve of studied microscopic image within TWS was obtained In the present study, different statistical results for precision value (97%), recall value (100%) and F-measure value (99%) were predicted.**Conclusion:** Automated microscopic image segmentation using deep learning can provide accurate, reproducible, and efficient prediction of cellular structures. Such approaches have considerable potential for computer-assisted microscopy, quantitative pathology, biomedical research, and clinical decision-support systems.

KEYWORDS

INTRODUCTION

The testing of nuclear abnormalities in fish cells is a potential protocol to evaluate the presence of genotoxins in waterbodies.[1] On the other hand, manual scoring with statistical interpretation is a tedious job. In this context, automated image analysis is beneficial solution to explore large numbers of microscopic images.[2]

The segmentation is the process of partitioning an image into multiple homogeneous parts or segments. Moreover, segmentation establishes a major transition in the image analysis pipeline, changing intensity values by region-based labels.[2]

The segmentation can be performed through machine learning algorithms.[2,3,4] An earlier study conducted by Sarrafzadeh and Dehnavi[5] detected leukocytes from a blood smear microscopic image and segmented these into their two dominant elements viz. nucleus and cytoplasm.

Tumour detection, tissue segmentation, histological image analysis, blood-cell categorization, and cell and nucleus segmentation are just a few of the microscopy applications for which deep learning-based segmentation has been employed. However, the quality and diversity of training data, annotation accuracy, imaging modality, staining protocol, and acquisition equipment can all have an impact on model performance.[6]

In Trainable Weka Segmentation (TWS) method, the popular image processing toolkit Fiji was combined,[7] with the state-of-the-art machine learning algorithms provided in the latest version of the data mining and machine learning toolkit Waikato Environment for Knowledge Analysis (WEKA).[8]

Thus, the objective of the study was to evaluate nuclear abnormalities through an automated deep learning-based technique segmented microscopic image by using quantitative segmentation measurements with statistical validation.

MATERIAL AND METHODS

Study design

A computational and image-analysis research was conducted by using microscopic image and their matching expert-generated segmentation annotations served as the foundation for this study design.

Image as dataset

The microscopic image of grayscale on nuclear abnormalities was selected from an earlier study by Mondal and Talapatra.[9]

Segmentation process

The segmentation of the input image was incorporated in Fiji-ImageJ tool of MS Window platform (version, 1.54n). After incorporation of image, plugin was selected for TWS (version-3.2.11) machine learning tool as per the study by Arganda-Carreras et al.[2] This tool transforms the segmentation method into a pixel classification where each pixel can be classified to fit into a specific segment or class. Herein, three classes were selected for the groups of cells. A set of input pixels that labelled, which is represented in the feature space and further used as the training set for a selected classifier. Once the classifier was trained, it was used to classify the rest of the input pixels. All methods available in TWS that was used. Finally, the results along with probability maps of three classes and Threshold curve with data were created in this tool.

RESULTS

Fig 1 exhibits three classes were selected in the studied microscopic image under train classifier within TWS.

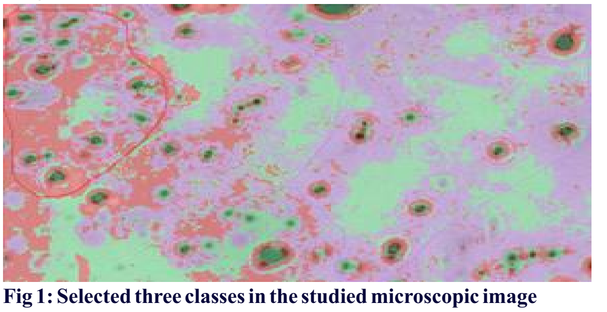

Fig 1: Selected three classes in the studied microscopic image

Fig 2 exhibits the studied microscopic image after train classified within TWS.

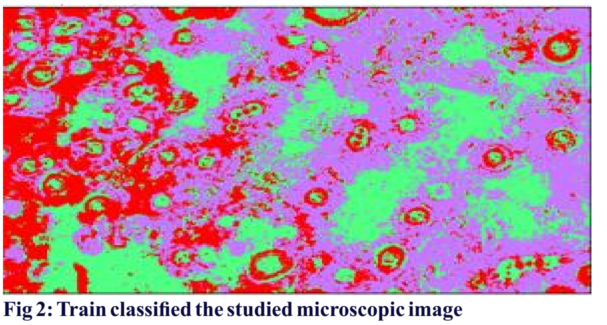

Fig 2: Train classified the studied microscopic image

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Fig 3 exhibits the probability map for three classes of studied microscopic image within TWS. In class 1 (10 cells), class 2 (14 cells) and class 3 (12 cells) in which 495x308 pixels were obtained.

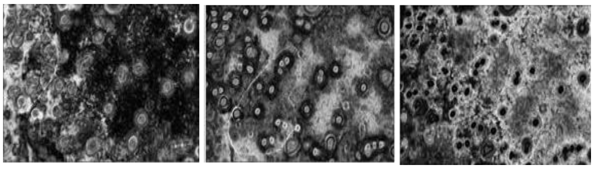

Fig 3: probability map for three classes in studied microscopic image

Fig 4 exhibits the threshold curve of studied microscopic image within TWS. In the present study, different statistical results for precision value (97%), recall value (100%) and F-measure value (99%) were predicted (Table 1).

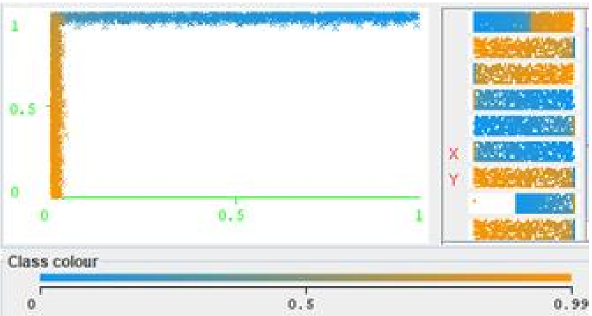

Fig 4: Threshold curve of segmentation for studied microscopic image

Table 1: Statistical results from threshold curve

Precision value	Recall value	F-measure value	Fallout value
97%	100%	99%	0.02

DISCUSSION

Accurate identification of cellular and tissue structures lays the foundation for subsequent quantitative evaluation; therefore, microscopic image segmentation is a crucial part of automated biomedical image analysis.[10] The current research evaluated a segmentation framework based on deep learning and showed that automated pixel-level segmentation may provide considerable concordance with expert-generated reference masks.

The performance of the model can be attributed as per the ability of convolutional neural networks (CNN) to learn hierarchical spatial and morphological features directly from image.[11] Deep learning models, as opposed to classic thresholding methods that rely heavily on pixel intensity, may integrate intricate contextual information such as shape, texture, borders, and spatial connections.[2]

Overlapping and contacting cells are a major difficulty in microscopic segmentation. Even experienced observers may disagree on their annotations when boundaries are ill-defined.[12]

Another crucial aspect to consider is the image's heterogeneity. Staining protocol, microscope maker, illumination conditions, magnification, camera attributes, and sample preparation can all have an impact on microscopic pictures.[13]

Automated microscopy segmentation has a lot of research and clinical uses. Quantitative values derived from segmented objects can aid in biomarker evaluation, morphological analysis, cell counting, treatment-response assessment, and disease classification. Furthermore, automated systems may improve analytical repeatability and shorten the time needed for recurring image-analysis tasks.[14]

In the present study, precision value (97%), recall value (100%) and F-measure value (99%) were predicted after segmentation, which was predicted lower for precision (91.4%), recall (92.7%) and F-score (91.8%) but the image was different as radiograph reported in a recent study.[15]

CONCLUSION

The present study evaluates the potential of microscopic image segmentation through deep learning-based method, which easily performed automated identification of cellular structures with the precision value (97%), recall value (100%) and F-measure value (99%), respectively.

Quantitative microscopic image analysis may be facilitated by automated segmentation, which may also lower manual workload and increase reproducibility. Challenges with image variability, overlapping structures, annotation quality, and external generalizability continue despite these benefits.

The tool TWS is a flexible to classify the pixels. It may be utilized as a pixel classifier for a variety of tasks, including boundary detection, semantic segmentation, and object detection and localization. Microscopic image segmentation has the potential to be a crucial element of digital pathology and biomedical workflows that are supported by artificial intelligence if it is properly validated.

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Declaration of conflicting interests

Authors declare no conflicts of interest.

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