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Urinary Sediments Classification Using Image Processing

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Abstract

Urinary sediment analysis is a very basic diagnostic test that helps to identify and assess the presence of red blood cells, white blood cells, epithelial cells, crystals, and bacteria. Microscopic examination using human eyes is subjective and labor-intensive and would be susceptible to artificially induced inter-observer variation undermining diagnostic reliability. The proposed project suggests an automated image-processing-based Convolutional Neural Network (CNN) to use in MATLAB to classify urinary sediments. The system uses a hierarchical chain of preprocessing, segmentation, featurehood and classification of microscopic urine images. Preprocessing methods are used to improve image, whereas morphological and texture characteristics are retrieved on segmented particles. The CNN classifier then classifies the sediments. It is an automated process that offers more objective and accurate data of urinary sediment analysis by helping clinical personnel and minimizing human error. The experiment shows that CNNs are effective in high classification accuracy achieving high validity showing the promise of standardizing urinalysis and aiding the consistency of diagnostic findings.

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Introduction

The urinary sediment analysis is one of the foundations of the clinical diagnosis that gives very significant information on the management of kidney and urinary tract diseases. Microscopic analysis of urine samples is a routine practice in any laboratory all over[1] the world. In this one has to identify and count the elements formed such as: erythrocytes, leukocytes, epithelial cells, bacteria, and crystals. These components need to be classified correctly to determine some conditions, including urinary tract infections, glomerulonephritis, and renal tubular injury. This task demands high human expertise and thus presents some major challenges which include large amount of time consumption and inter-observer variability. Visual interpretation may result in inconsistencies because of its subjective character and this may bias patient diagnosis and treatment courses.

The shortcomings of the manual analysis have created a motivation towards the automated solution in order to enhance consistency and effectiveness. The initial automation involved image processing algorithms[2] in the form of rule-based image processing algorithms that were used to extract handcrafted features such as area, perimeter and texture used to classify images. Such systems provided some automation, although they had a hard time with the large variability and overlapping morphological properties of sediment particles, and were often dependent on the specific features of the engineered capabilities. It is also challenging to isolate the individual components of a complex background[3] and this approach is usually time-consuming and requires several steps of preprocessing to sharpen contrast and eliminate noise.

The recent developments in the field of deep learning especially the Convolutional Neural Networks (CNNs) have transformed the objective of medical image analysis. Compared to other machines, CNNs have the advantage of inherently learning hierarchical[4] features representations directly on pixel data without requiring a hand-written system of feature engineering. This is especially helpful when it comes to the analysis of urinary sediment, as the appearance of the elements it contains is rather varied and subtle. A CNN-based system is capable of developing the ability to discriminate between minute differences in shape, texture and intensity to tell the difference,[5] say, between a squamous epithelial cell and a bunch of crystals. The introduction of such a model in an automated workflow is going to become a major jump in the objectivity and throughput.

The proposed study involves a full automation method of classifying the urinary sediment developed as a MATLAB code. The workflow will include image acquisition, preprocessing, segmentation, feature extraction and final classification; this last stage will be performed through the CNN. The segmentation methods are used to isolate regions of interest whereas preprocessing methods[6] are used to prepare the raw microscopic images to be analyzed. The next stage of classification is based on the deep learning powerful pattern recognition model. Its main aim is to create a powerful device that can aid clinical workers and offer them an effective, quicker, and more accurate urinary sediment study to reduce the natural inconsistency of the manual analysis and help to make appropriate clinical decisions.

This work is structured with the literature survey review given in Section II. Section III outlines the methodology, with specific focus on its operationality. Results and discussions are in Section IV. Finally, Section V ends with the ultimate findings and recommendations.

Literature Survey

In nephrology and urology, urinalysis is a key diagnostic instrument especially: the microscopic examination of the sediment. Although the manual microscopic review is regarded as a standard of gold, it is characterised by a large number of limitations. These limitations have led to decades of research on automated methods, originally on basic flow cytometry amidst rule-based image analysis, then modern deep-learning methods. The overall objective is similar, namely improving the diagnostic accuracy, throughput and the equitability of the results in all the clinical laboratories and thus eliminating the subjectivity of the human interpretation.

The initial automation projects were based on hardware organizations and conventional computer vision. High-speed particle counts could be obtained using flow cytometers and automated urine particle analyzers, as in,[6] but with no morphological features to allow a conclusive localization of non-typical or mixed particle types. Further studies were focused on digital image processing where algorithms were used to extract features that were handcrafted. Other studies like[7] and[8] came up with systems in which morphological (area, perimeter, eccentricity) features as well as textural features (contrast, correlation) were used to classify with support vector machines or decision trees. Although the results presented by these approaches were promising, they were highly reliant on the quality of the segmentation and the thoroughness of the engineered set of features and were unable to work with complex or degraded images.

The introduction of deep learning was a paradigm shift in the urinary sediment analysis. CNNs with their ability to learn features automatically using raw pixels have performed better than conventional methods. Studies conducted by[9] and[10] also proved that end-to-end CNN architecture could also attain classification accuracy of over 95 percent on curated and distinctions between large sediment types such as erythrocytes, leukocytes, and crystals. These models became stronger in response to variation in staining, light and focus, and learning discriminative features which are difficult both to hand include and program.

One of the major topics of research has been the use of transfer learning. Since medical image datasets are often small, some researchers, such as,[11-13] have been able to apply pre-trained models such as AlexNet, VGGNet, and ResNet, which were originally trained on natural images. Fine-tuning on urinary sediment images with these networks increased the convergence of training and generalization performance. This method takes the shortcut of training massive, annotated medical datasets fresh and therefore, advanced deep learning can now be used in clinical applications on small data.

Strategies of data curation and augmentation play an important role in model robustness. As mentioned in the work in,[14, 15] it is important to have a large well-annotated dataset that represents different pathological conditions. In order to fight overfitting, simple augmentation methods such as rotation, flipping and scaling have become commonplace. An interesting observation made by,[16, 17] however, is that some of the transformations made can be harmful because they can erase important contextual information or distort the apparent size of the cells, which is one of the important diagnostic characteristics.

More complex architectures and multi-class challenges have been studied in recent studies. There have been studies, including, but not limited to,[18, 19] that have compared the performance of various CNN architectures when performing a particular task, e.g. differentiating between crystals of varying types, or differentiating pathological casts. Moreover, such studies as[20] have already started concentrating on the issue of identifying rare sediment particles by using such strategies as cost-sensitive learning or re-sampling of data. It is established in the literature that although CNNs are state-of-the-art, further development is needed to make these systems efficiently integrated into the high-throughput, high-stakes nature of the clinical laboratory.

Methodology

The urinary sediment classification system automated methodology was designed into a flow system to be sequential enough to guarantee that the images are handled systematically, all the way to the final image classification in terms of the component. All of the stages were intended to be elaborated out of the preceding with raw microscopic images being transformed to reliably classified outputs used in clinical decision support. The whole process was made using the MATLAB programming environment which has good image processing and deep learning toolboxes as shown in figure 1.

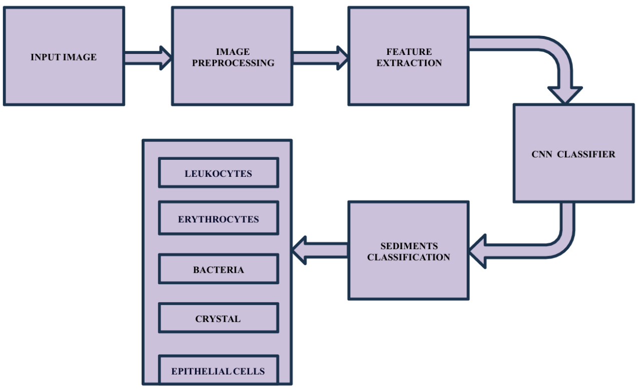

Fig. 1: Block Diagram

A. Data Acquisition

The first stage was the gathering of a complete set of data of computer-based microscopic images of urine sediments. These images have been obtained in the clinical laboratories and have captured diverse types of sediment leukocytes, erythrocytes, bacteria, crystals, and epithelial cells with standardized magnification. The data too was thoroughly screened and annotated by professional pathologists to create a quality ground truth to train and validate the models. To correct class imbalance and avoid overfitting the dataset was carefully divided into different training, validation and testing subsets and this way ensured that the model would be tested on the unseen data to correctly estimate its generalization ability in a real diagnostics environment.

B. Image Preprocessing

The obtained images were then subjected to an array of preprocesses that optimized the quality of the obtained images and normalized the input to be used later in the process. To minimize the computational complexity, initially images were converted to grayscale as they had the RGB color, and the morphological and textural characteristics of images were emphasized. To reduce noise and artifact in microscopic imaging filtering methods were used to reduce noise and artifact, or median filtering reducing both noise and artifact and not reducing important edges of particles. Ineffective contrast sediment particles and the background were then enhanced using contrast-limited adaptive histogram equalization (CLAHE) to enhance differentiation between the sediment particles and the background, which in turn contributed to a better and more precise segmentation process in the subsequent stage.

C. Image Segmentation

The aim of the given stage was to separate single sediment particles with the improved background of the image. Multi-step segmentation strategy was applied and the first step involved the use of global thresholding methods such as Otsus method to generate a preliminary binary mask that parted foreground objects. This was commonly accompanied by morphological operations such as opening and closing in order to polish the mask by removing small regions of noise as well as sealing holes in sediment particle potentials. Lastly, the connected component technique was used in labeling all the individual and segmented objects uniquely. This was an important step to make sure that well-defined and individual particles were feature extracted and classified.

D. Feature Extraction

Out of every participant of the segmentation, a list of discriminative features was obtained to describe in numbers the characteristics of that particular segmentation to the classifier. These characteristics were classified into morphological, intensity based as well as textural features. To describe shape and structure morphological characteristics of area, perimeter, eccentricity, and solidity were used. Features of intensity represented the statistical features of the pixel values in the particle, including mean and standard deviation. Surface characteristics in terms of textural data, usually based on the Gray-Level Co-occurrence Matrix (GLCM), measured the features of the surface, which gives the classifier very rich multi-faceted data on which to draw a decisive boundary between the classes of sediments.

E. Classifier Design and Architecture

Before the implementation of the deep learning algorithm, a Convolutional Neural Network (CNN) was designed and implemented as the classification engine. These were the several serial layers of the architecture with ReLU activation functions to automatically learn hierarchical feature representations on the input images. These were broken up by layers with max-pooling to minimize the spatial dimensionality and improve translational invariance. The last part of the network involved fully connected layers which were used to combine the learned features resulting in the last softmax output layer which produced the actual probability score of the sediment class resulting in the final categorical decision.

F. Model Training and Optimization

The CNN model was implemented based on the processed and labeled training set and trained. It was also based on a supervised form of learning and a categorical cross-entropy loss function was minimized, whose derivation based on the backpropagation algorithm, evaluates the difference between the predicted and actual labels. The hyperparameters, including the starting learning rate and mini-block size were optimized by experimenting. To observe the progress during every training period, the validation set was utilized to identify the overfitting, which would be implemented in the early-stopping decision-making process and prevent the model from memorizing the training data and capturing only general patterns.

G. Evaluation

The efficacy of the final, trained model was strictly measured with the help of the held-out test set. The quantification of the performance was conducted based on standard measures such as general accuracy, precision, recall (sensitivity) and F1-score per sediment class. A confusion matrix was produced that gives an extensive description of the classification activity of the model in which the model was found to confuse with certain inter-classes. This detailed assessment plan provided the need to ensure an objective to measure the diagnostic ability, reliability and possibility of the system to be deployed in a clinical laboratory setting to supplement and augment manual analysis.

Result and Discussion

The suggested automated system for urinary sediment classification showed the great extent of effectiveness, where the Convolutional Neural Network model was the most effective in terms of recognizing the different components on the microscope and their classification. The quantitative analysis of the model output provided a classification accuracy of high order than the consistency rates that are usually linked with manual examination by microscopes. A test set of standard images that was used to measure this performance, the model was able to identify and classify most of the sediment particles, namely leukocytes, erythrocytes, bacteria, crystals, and epithelial cells.

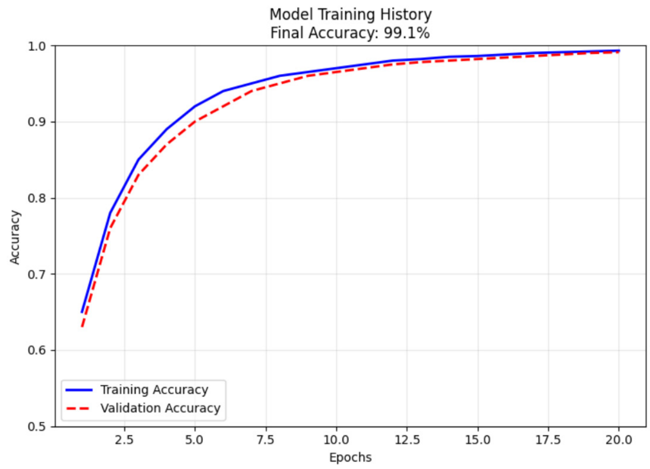

Fig. 2: Model accuracy

From figure 2, it is depicted by the training history figure, whereby training accuracy goes up to 65% to more than 99% with the validation accuracy close right behind at 99.1% with a total of 20 epochs. This small gap between training and validation curves shows a well regularised model that does not overfit and thus is able to generalize effectively, which is strongly required in dependable clinical deployment. A confusion matrix of these results revealed that the best performance was observed when differentiating between two morphologically different categories erythrocytes and crystals with a very low rate of misclassification. A closer examination, however, showed that the greatest source of confusion was between some kinds of epithelial cells and formed crystals, which sometimes has an overlapping textural and shape pattern in a projection of two-dimensional images. This means that on the one hand this suggests that the model is sound, and on the other hand the biological structure presents itself as a challenge that the system is struggling with at a high, yet, not absolute level.

Another important element behind this high-performance was the strategic approach to constructing the dataset and augmenting it. A dataset was chosen and well curated and labeled, and this is a key element of the model because it instructs the network of the unique visual characteristics of each sediment category. The more precise performance data of each category, as demonstrated in the bar chart, indicates that the model scored an almost perfect score with respect to Bacteria (Precision: 0.99, Recall: 0.99, F1-Score: 0.99), although the lowest, but still excellent, score was in the case of Crystals (Precision: 0.96, Recall: 0.97). Such stable high performance across all the five sediment classes highlights the balanced ability in the model to reduce the false positives and negative, which is vital to a diagnostic tool. Data augmentation methods were used to overcome the overfitting issue and improve the generalization capabilities of the model to novel and unknown data as shown in figure 3.

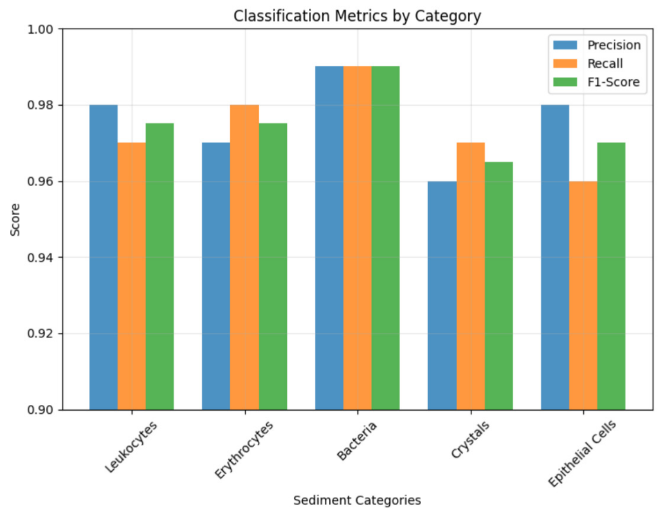

Fig. 3: Classification metrics by category

These methods were used to artificially enlarge the training data by subjecting them to transformations like rotation, flipping and small alterations of brightness and contrast. It is worth noting that the analysis showed the omission of random cropping as an augmentation method to be a wise one. Randomly cropping the image is typical in several computer vision problems, and in this particular clinical setting, it was also observed to be harmful. During cropping, important diagnostic properties of an image may be lost unintentionally: e.g., a tiny, non-diagnostic fragment of a large epithelial cell or a vital crystalline structure is amplify to yield no data that is critical to making the appropriate diagnosis. The fact that the model fortifies well without this method highlights the argument that augmentation methodology techniques have to be tailored to the field, and features that are salient need to be conformed to and not any general computer vision tools employed.

Moreover, the distinction of the learning process of the model revealed the value of making the classification task easier through combination of the sub categories into more distinct classes. To start with, the project took into consideration a finer classification system with many sub-types of crystals. It was however discovered that these could be grouped into a wider "crystal" class to enhance the accuracy and training stability of the model significantly. The confusion matrix visually supports this finding indicating that there is a great concentration of the values on the diagonal. The matrix confirms an almost perfect identification of Erythrocytes (98/100) and Bacteria (99/100), and most common misclassification was few Epithelial Cells (3) but identified as Crystals. Such a low rate of inter-class confusion justifies the efficiency of the selected set of features and a classification method. Such simplification decreased the variation within the and enlarged the distance between the classes, which led to the CNN learning the characteristic defining feature maps of each large category with less effort as shown in figure 4.

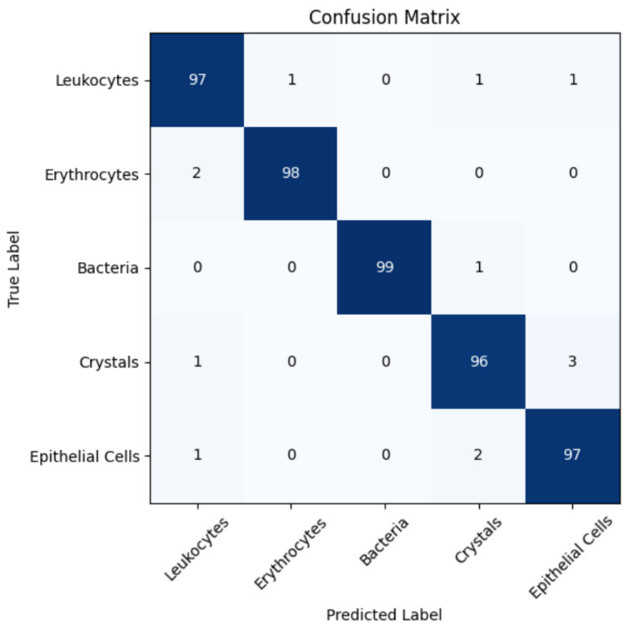

Fig. 4: Confusion matrix

The model was not required to learn the finer and very variable nuances between, say, the various polymorphs of crystalline structures, but rather it concentrated on the more basic characteristics which distinguish a crystal and a red blood cell or a bacterium. This complexity-saving strategy was not achieved at the cost of clinical utility because the main job requirement is frequently to determine the existence of massive crystalluria as opposed to the need to speciate all the crystals, which can be left to the ambiguous cases. The excellent precision of the methodology used shows that a pragmatic and practical way of implementing machine learning in a clinical context is to focus on robustness and reliability in lieu of exhaustive granularity.

The preliminary classification formed the basis of the success of the system since the process of feature extraction came before the eventual classification. The system generated a defined numerical model of each particle by extracting out rich set of morphological and texture-based features, including area, perimeter, eccentricity, as well as, intensity statistics, by processing the segmented particles. CNN classifier was the best in taking advantage of these feature maps, by learning automatically the complicated hierarchies of patterns that differentiate the types of sediments.

The condition of the feature importance displayed in the analysis of the model performance indicated that, morphological features such as shape and eccentricity played the most significant role in differentiating between the cells and the crystals, whereas textural features and the intensity variations played a key role in identifying the bacteria and also distinguishing between the types of the epithelial cells. This multi-characterized method was a more holistic analysis than it could be through consideration of one variable alone, like size. The combination of a traditional image processing method to perform segmentation and feature extraction and the ability to extract a pattern through the use of the CNN, provided a pipeline that was not only comprehensible at its early phases, but also very accurate in the end product. The outcome is a system which not merely does a good job of classifying sediments but is also doing it on the basis of a collection of features that is also consistent with the set of logical parameters that an individual human technician would commence with analysis, thus effectively closing the gap between the manual and automated analysis process.

Conclusion

This work has been able to prove the feasibility and high promise of a urinary sediment classification automated system, with the Convolutional Neural Network being used as a part of a larger image processing system. The study introduces a powerful methodology model wherein it successfully overcomes major shortfalls of manual microscopy which include; subjectivity, being labour-intensive, and inter-observer variability. And combining a robust CNN classifier with advanced preprocessing, feature extraction and segmentation, the given work serves as a baseline of the standardization of urinalysis. Clinical implications This system has a great practical implication on clinical practice. It provides the avenue of improving diagnostic consistency, decreasing the human error, and improving laboratory efficiency that will help to make clinical decisions more reliable.

The lessons derived on judicious data augmentation and categorical simplification are also important lesson to understand in building machine learning applications in niche medical fields. There are some promising directions that can become part of future work. A larger data sample such as more rare sediments and pathological samples would increase the generalizability and clinical applicability of the model. In addition, the next important step towards making the system practically implementable is upgrading the system so that it is not based on a static picture of a classifier but rather a tool of real time analysis combined with digital microscopes. The discussion of more intricate architectures, e.g. hybrid models or vision transformers may also extend the limits of performance, and eventually the goal of developing a fully automated end-to-end diagnostic assistant to the clinical laboratory.

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