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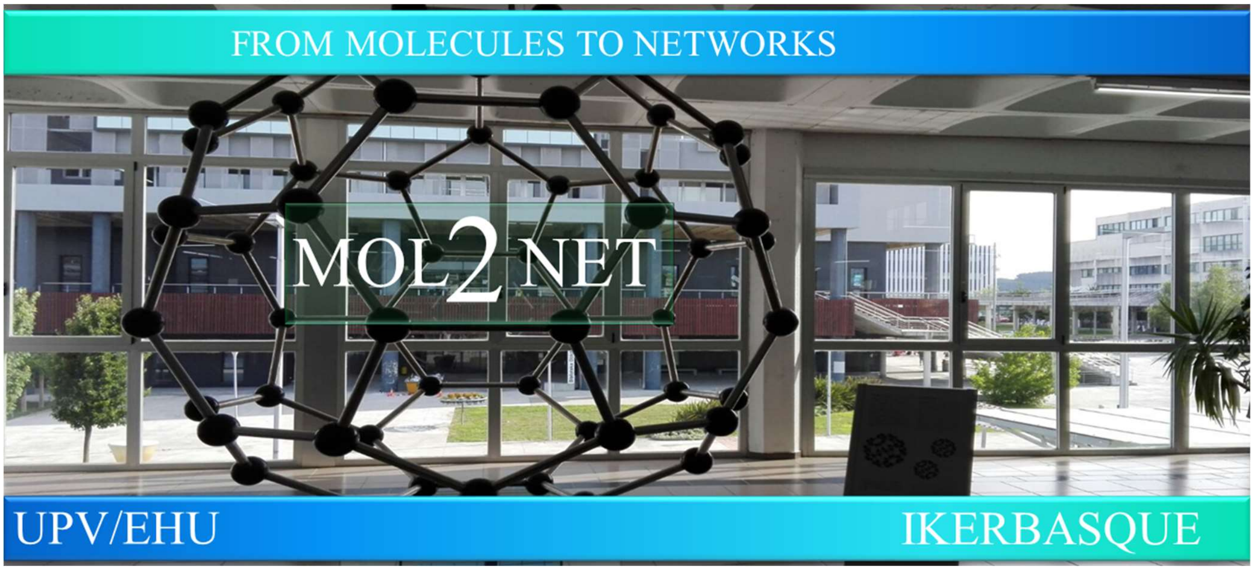

Analysis and Identification of Nephrolithiasis from Ultrasound Images using Machine Learning Approach

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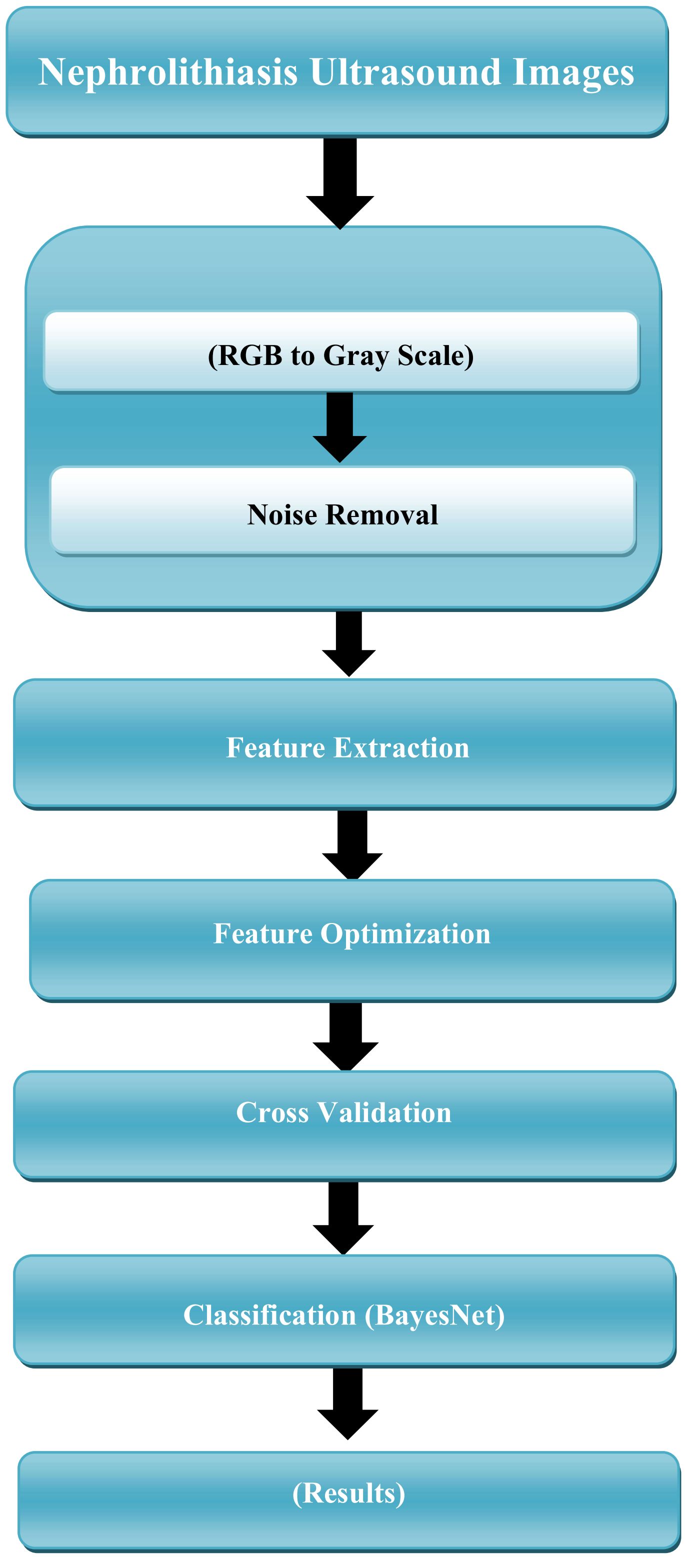
Abstract.

Nephrolithiasis, commonly known as kidney stone disease, is a disorder in which the deposition of certain minerals causes a stone to develop in the urinary tract. Urolithiasis is another name for nephrolithiasis. Most of the time, kidney calculi form in the renal system and are eliminated through the urine system. Even a tiny stone can readily travel through the urine without any issues. More than 5 millimeters (0.2 inches) in diameter, fully grown calculi can clog the urinary tract, which can cause intense pain in the lumbar region or the stomach. Calculi can result in problems such as dysuria, vomiting, and hematuria. The recommended approach for automatically segmenting kidney stones is based on a four-stage framework, the first of which calls for pre-processing kidney pictures for better enhancement and is followed by the active contour method for automatically segmenting kidney stones. In the future, an assessment will be performed depending on the size and kind of stone.

Keywords: Nephrolithiasis, Ultrasound, Machine Learning, Classification.

Graphical Abstract



Introduction

The medical word for kidney stones is nephrolithiasis. Nephrolithiasis refers to the process through which kidney stones are formed in the kidney. *Nephrolithiasis* is a chronic kidney disease that may affect either kidney. "Nephrolithiasis" comes from the Greek words "Nephros" (which means kidney) and "Lithos," which means "stone" (stone) [1]. Nephrolithiasis may vary from as little as a single grain of sand to as big as a single salt particle. Nephrolithiasis is sometimes referred to as the "silent killer" because kidney stones often do not cause any symptoms during their development; however, as they continue to grow, they disrupt the normal functioning of the kidneys, and ultimately, surgery is required to remove the stones in order to lower the risk of kidney failure. *Nephrolithiasis* is a frequent condition that may cause discomfort in the abdominal region, pain in the patient's low back and side, blood in the urine, nausea, and vomiting [2]. Nephrolithiasis affects one out of every ten persons at some point in their lives. *Nephrolithiasis* is a condition that occurs when there is an increase in the number of compounds that might form stones, such as calcium, oxalate, uric acid, or cystine. Nephrolithiasis running in one's family is another factor that might lead to the development of kidney stones. Nephrolithiasis may also be caused by dehydration, chronic conditions such as cardiovascular diseases (CVD) and diabetes, environmental factors, and certain drugs. Dehydration is another risk factor. Patients suffering from nephrolithiasis are more likely to be of Asian, American, or African descent [3].

Nephrolithiasis illness is one of the hazards to life that can be found all over the globe. The majority of individuals who have these diseases of the kidney initially do not identify it as a disease, and it causes damage to the organs in a very gradual manner. Before evaluating their symptoms, many individuals were impacted by renal failure often. *Nephrolithiasis* is a condition that affects anywhere from one percent to fifteen percent of persons at some point in their life (Morgan MS, Pearle MS) [4]. Kidney stones have steadily increased in incidence throughout Western populations since the 1970s. According to the data collected in 2015, there were 22.1 million kidney stones, which resulted in the deaths of around 16,100 people suffering from nephrolithiasis. Compared to men, females are more likely to be impacted by nephrolithiasis and are more likely to have the condition. Kidney stones have been a problem for humans for as long as recorded history goes, and surgical procedures to treat and remove the stones date back to at least 600 BC [5].

The nephrotic syndrome should be diagnosed as soon as possible since it may lead to kidney failure, which can be fatal if left untreated. Nephrolithiasis is presumed to be the underlying cause of a patient's symptoms when particular symptoms are present. All other potential causes of the patient's low back pain or stomach discomfort have been ruled out. It is debatable which test would be the most accurate in identifying nephrolithiasis. Primarily In order to diagnose nephrolithiasis, imaging tests are performed [6]. Nephrolithiasis is diagnosed in most patients who visit the emergency department of a hospital by doing a Kidney, Ureter, and Bladder (KUB) Ultrasound, followed by a non-contrast CT scan and, finally, an X-ray. Nephrolithiasis may be effectively diagnosed by using ultrasound as the first diagnostic step. CT scans, on the other hand, subject patients to severe radiation exposure. Because it is also one of the non-invasive low-cost imaging methods, ultrasound picture is one of the most extensively utilized imaging modalities for diagnosing renal problems [7-8].

Figure 1: Images of KUB Ultrasound, X-Ray and non-contrast CT scans (en.wikipedia.org)

Materials and Methods

The extraction of certain features makes use of a wide variety of strategies and procedures for the preprocessing of images in order to get the best possible results. The proposed approach, together with CVIPtools version 5.6e and WEKA, was used to achieve the results obtained and discussed in this section [9-10]. These are the most effective software applications for feature selection and results generation in image processing, notably in the medical sciences. The first step is to compile a data set consisting of one hundred photographs of patients from the United States. These photographs are separated into two groups: patients with normal kidney function and patients with renal problems. A piece of these categories has fifty images. A dataset includes each of the one hundred images shot in the United States. In the next step, these photographs are put to use in CVIPtools after first being edited using an image editor to have their dimensions customized for use online by cropping and reducing them. The photographs that are cropped and then converted to grayscale are considered utilities. After each of the one hundred photographs has been cropped, downsized, and individually converted from color to black and white, they are arranged in a circle to locate the best possible location [11]. Using return on investment to decide on a specific region Each image consists of six circles, each of which has a width and height of 512 by 512 pixels, a beginning column and row of 128 by 128, and a blur radius of 32 by 32 pixels. The addition of 16 values to each image causes the row and column to shift, resulting in a total of 600 ROI being generated from the original 100 pictures. By keeping the width, height, and blur radius constant throughout all images, six ROIs may be produced from each. This ROI is captured by selecting several characteristics, including binary, histogram, and texture features, for a total of 21 features. A text file is first constructed and then used in the WEKA software. It is converted into a CSV file and an arff file. Finally, more results are produced utilizing the text file.

Results and Discussion

- Classification model: BayesNet
- Time taken to build the model: 0.14 seconds
- Test mode: 10-fold cross-validation

Table 1: BayesNet Classifier Summary

Total Number of Instances	600	
Correctly Classified Instances	581	**96.8333 %**
Incorrectly Classified Instances	19	**3.1667 %**
Kappa statistic	0.9367	
Mean absolute error	0.0302	
Root mean squared error	0.1542	
Relative absolute error	6.0474 %	
Root relative squared error	30.8391 %	

Table 2: BayesNet Classifier Detailed Accuracy

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	Class
0.963	0.027	0.973	0.963	0.968	0.937	0.997	**Normal**
0.973	0.037	0.964	0.973	0.968	0.937	0.997	**Abnormal**
0.968	0.032	0.968	0.968	0.968	0.937	0.997	**Weighted Avg.**

Table 3: Confusion Matrix using BayesNet Classifier

Classified as	A	B
A = Normal	289	11
B = Abnormal	8	292

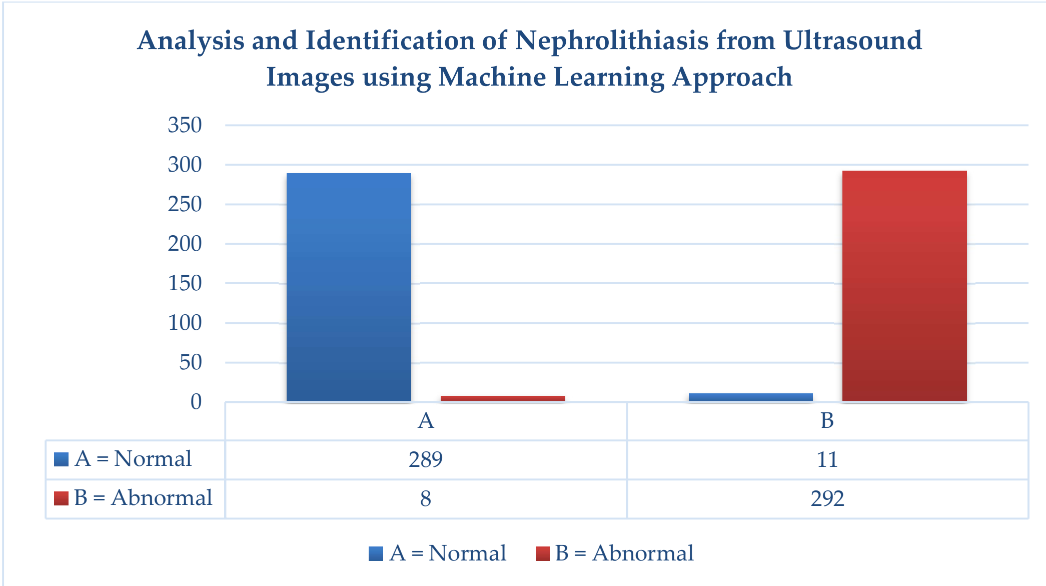


Figure 2: Accuracy of Dataset using BayesNet Classifier (10-Fold)

Conclusions

Regardless of some challenges, "kidney Nephrolithiasis identification using machine learning" is a most important field. Regular and some optimized algorithm of feature extraction extracts Nephrolithiasis features. The percentage split and cross-validation methods of machine learning are applied to these optimized features. After the training and testing of the processed data, we applied some best classifiers to differentiate the regular and Nephrolithiasis reading of the dataset. We achieve a maximum of 96.83 % results with BayesNet. Some optimized machine learning and machine vision methods can improve the results' accuracy regarding differentiating the Nephrolithiasis and normal area in the 2D US.

References

[1]. George, M., & Anita, H. B. (2022). Analysis of kidney ultrasound images using deep learning and machine learning techniques: A review. Pervasive Computing and Social Networking, 183-199.

[2]. Ma, F., Sun, T., Liu, L., & Jing, H. (2020). Detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artificial neural network. Future Generation Computer Systems, 111, 17-26.

[3]. Verma, J., Nath, M., Tripathi, P., & Saini, K. K. (2017). Analysis and identification of kidney stone using Kth nearest neighbour (KNN) and support vector machine (SVM) classification techniques. Pattern Recognition and Image Analysis, 27(3), 574-580.

[4]. Cui, Y., Sun, Z., Ma, S., Liu, W., Wang, X., Zhang, X., & Wang, X. (2021). Automatic detection and scoring of kidney stones on noncontrast CT images using STONE nephrolithometry: combined deep learning and thresholding methods. Molecular Imaging and Biology, 23(3), 436-445.

[5]. Yildirim, K., Bozdag, P. G., Talo, M., Yildirim, O., Karabatak, M., & Acharya, U. R. (2021). Deep learning model for automated kidney stone detection using coronal CT images. Computers in biology and medicine, 135, 104569.

[6]. Sassanarakkit, S., Hadpech, S., & Thongboonkerd, V. (2022). Theranostic roles of machine learning in clinical management of kidney stone disease. Computational and Structural Biotechnology Journal.

[7]. De Perrot, T., Hofmeister, J., Burgermeister, S., Martin, S. P., Feutry, G., Klein, J., & Montet, X. (2019). Differentiating kidney stones from phleboliths in unenhanced low-dose computed tomography using radiomics and machine learning. European radiology, 29(9), 4776-4782.

[8]. Somasundaram, D. (2022, October). Machine Learning Algorithm for Abnormality Detection and Classification of Kidney Stones in Ultrasound Images. In 2022 IEEE 3rd Global Conference for Advancement in Technology (GCAT) (pp. 1-3). IEEE.

[9]. Naeem, S., Ali, A., Qadri, S., Khan Mashwani, W., Tairan, N., Shah, H., ... & Anam, S. (2020). Machine-learning based hybrid-feature analysis for liver cancer classification using fused (MR and CT) images. Applied Sciences, 10(9), 3134.

[10]. Ali, A., Mashwani, W. K., Naeem, S., Uddin, M. I., Kumam, W., Kumam, P., ... & Chesneau, C. (2021). COVID-19 infected lung computed tomography segmentation and supervised classification approach.

[11]. Ali, A., Qadri, S., Khan Mashwani, W., Kumam, W., Kumam, P., Naeem, S., ... & Sulaiman, M. (2020). Machine learning based automated segmentation and hybrid feature analysis for diabetic retinopathy classification using fundus image. Entropy, 22(5), 567.