ORIGINAL RESEARCH

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Analysis and Comparison of Kidney Stone Detection using Parallel Piped Classifier and Bayesian Classifier with Improved Classification Accuracy

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ABSTRACT

Aim: The goal of this research is to use parallel piped classifiers and bayesian classifiers to predict and detect kidney stones. Materials and Methods: This investigation made use of a collection of data from Kaggle website. Samples were considered as (N=10) for parallel piped classifiers and (N=10) for bayesian classifiers according to clinicalc.com, total sample size calculated. The accuracy was calculated by using MATLAB with a standard data set. Pretest G power taken as 85 in sample size calculation can be done through clinical.com. Results: The accuracy (%) of both classification techniques are compared using SPSS software by independent sample t-tests. There is a significant difference between the two classification techniques. Comparison results show that innovative parallel piped classifiers give better classification with an accuracy of (83.5410%) than bayesian classifiers (71.1314%).There is a statistical significant difference between parallelepiped classifiers and bayesian classifiers. The parallel piped classifiers with $p=0.007$, $p<0.05$ significant accuracy (83.54%) showed better results in comparison to bayesian classifiers. Conclusion: The parallel piped classifiers appear to give better classification accuracy than the bayesian classifiers.

Keywords

Kidney Stone, Image Classification, Classifier, Innovative Parallel Piped Classifier, Bayesian Classifier, Machine Learning

Imprint

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INTRODUCTION

The study helps to develop a method for detecting kidney stones using parallel piped classifier and bayesian classifier (Ardon et al. 2015). Kidney stones are a common problem throughout the world, and their rate is increasing every year. There are a variety of kidney stone detection techniques aimed at determining the reason for their creation.The majority of them, however, are time consuming, difficult, and costly. One of the most significant operations in surgical and therapeutic planning is the detection and segmentation ofidney stones for ultrasound imaging. The accuracy of the diagnosis is critical for providing the right medication to get treatment of the stones and prevent future symptoms. However, in actual practice, kidney stone segmentation in ultrasound pictures is now primarily done manually (Viswanath and Gunasundari 2017). As a result, there is a need to develop a kidney stone detection system based on classifiers technique. In this research a parallel piped classifier along with bayesian approach was tried to classify kidney stone detection (Harris, Fontanarosa, and Verhaegen 2021).

This study has been linked to 34 google scholar and 150 science science direct articles (Schulsinger 2014). In recent years related to medical images many classification methods, and models utilizing machine learning have been reported with one of its performance measures as classification accuracy. An image access through the performance measure of parallel piped classifiers accuracy (95.12%) and bayesian classifier accuracy (78.56%) has been encoded with machine learning which is the easiest and simplest method to form the detection of kidney stone (Al-Gburi, Ibrahim, and Zakaria 2020).Our team has extensive knowledge and research experience that has translate into high quality publications (Chellapa et al. 2020; Lavanya, Kannan, and Arivalagan 2021; Raj R, D, and S 2020; Shilpa-Jain et al. 2021; S, R, and P 2021; Ramadoss, Padmanaban, and Subramanian 2022; Wu et al. 2020; Kalidoss, Umapathy, and Rani Thirunavukkarasu 2021; Kaja et al. 2020; Antink et al. 2020; Paul et al. 2020; Malaikolundhan et al. 2020)

The goal of this research is to use parallel piped classifiers and bayesian classifiers to predict and detect kidney stones at an early stage. The parallel piped classifier algorithm exceeds the bayesian classification algorithms in terms of accuracy, achieving 83.54%.

MATERIALS AND METHODS

The study was conducted in a simulation lab at Saveetha School of Engineering and samples were collected from Kaggle website where ethical approval is not necessary. The samples are separated into two groups and tested for kidney stone detection using parallel pipes and bayesian classifiers. Each group has a size of 20 samples. Pretest G power sample size calculation can be done through clinicalc.com. The alpha error is 0.05 power: 85, Beta: 0.2 with 95% confidence interval.

The findings of both the algorithms are validated by statistical analysis. IBM SPSS software was used for statistical analysis. The independent variable correlation was tested using an independent sample t-test. First, the input images were rescaled to 512x480 pixels. Following that, a parallel piped classifier and a bayesian classifier algorithms using Matlab software were used to extract features to classify kidney stone images. In Matlab programming, the estimated sample values are exported for statistical analysis. Then it is trained with features of all the images instead of individual images and while testing rather than the predicted label of the testing image a whole label of obtained features is predicted. If the image of the majority of features was matching with that of the expected image then it was a successful recognition. The performance of both algorithms was measured using the classification accuracy on kidney stone images. This parameter was calculated and evaluated to assess the method's efficacy and comparison of results was done for both methods to find which algorithm performed significantly better results (Dinesh Peter et al. 2019).

Statistical Analysis

To validate the results of both algorithms, statistical analysis was done using IBM-SPSS software. As the two classifiers are independent to each other, independent samples t-test was performed for the independent variable classification and detection. The accuracy is a dependent variable in this study.

RESULTS

Table 1. represents the comparison of mean accuracy value of innovative parallel piped classifier and bayesian classifier of sample kidney stone images. Table 2. shows a group statistics comparison of parallel piped classifier and bayesian classifiers based on accuracy. The mean value of accuracy is high (83.5410%) for parallel piped classifier and low (71.1314%) for bayesian classifier. The standard deviation error of mean accuracy is low for parallel piped algorithm (.92903) and high (2.13782) for bayesian technique.

Table 1

Accuracy (%) values of parallel piped classifier and bayesian classifiers of sample kidney stone images

Samples	Classification Accuracy (%)	
	Parallelepiped Classifier	Bayesian Classifier
1	81.2	71.106
2	83.51	73.21
3	83.52	69.51
4	83.51	80.01
5	82.3	62.5
6	81.01	71.118
7	80.95	73.21
8	82.36	69.51
9	83.54	80.01
10	81.01	62.5
11	99.99	62.5
12	83.51	52.43
13	83.52	52.9
14	83.51	71.134
15	82.3	73.218
16	81.02	69.51
17	80.95	80.01
18	82.36	72.52
19	83.54	90.312
20	87.21	85.41

Table 2.

Group statistics show a comparison of parallel piped classifier and bayesian classifiers based on accuracy. The mean value of accuracy is high at 83.5410% for parallel piped classifier and low at 71.1314% for bayesian classifier. The standard deviation error of mean accuracy is low for parallel piped algorithm (0.92903) and high (2.13782) for bayesian technique.

	Group	N	Mean	Standard Deviation	Standard Error Mean
Accuracy	Parallel piped classifier	20	83.5410	4.15477	.92903
	Bayesian classifier	20	71.1314	9.56062	2.13782

Table 3. represents the independent sample t-test which compares the two independent groups (parallelepiped and bayesian). The data was statistically significant between the two groups. It provides mean difference, significance value (2-tailed) standard error

Table 3

Independent sample t-test provides mean difference, significance value (2-tailed) standard error difference, and 95% confidence interval of the difference in both lower and upper levels for accuracy at equal variances assumed and not assumed. Independent Sample t test shows comparison between parallel piped and bayesian classifiers.

Parameters		Leven's test for equality of variance		T-test for equality of variance					95 % of the confidence interval of the difference		
		f	sig	t	df	One tailed p	Two tailed p	Mean diff	Std. Error Diff	Lower	Upper
Accuracy	Equal variances assumed	8.079	0.007	5.324	38	.0001	.0001	12.04960	2.33096	7.69082	17.12838
	Equal variances not assumed			5.324	25.929	.0001	.0001	12.40960	2.33096	7.61761	17.20159

difference, and 95% confidence interval of the difference in both lower and upper levels for accuracy at equal variances assumed and not assumed. It portrays the mean and standard deviation of the two parameters, t-test equality of variance and 95% confidence interval. This study has different (N=20) samples, the mean difference in equal variances assumed and equal variances not assumed with the upper and lower (mean difference 12.40960) and the relation of std. error difference (2.33096) also been considered along with the correlation between t- test.

Figure 1 represents Matlab simulation results of parallel piped classifier and bayesian algorithm (a) Input image (Kidney stone image), (b) Classification result of parallel piped classifier and (c) Classification result of bayesian classifier.

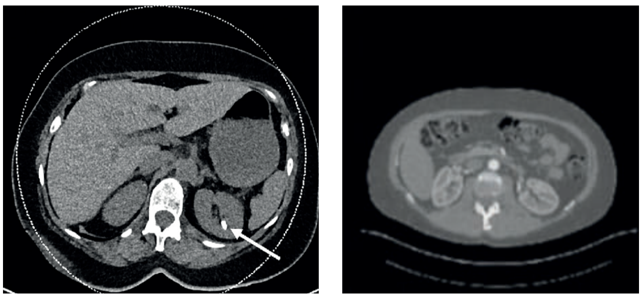

Fig. 1. Matlab simulation results of parallel piped classifier and bayesian algorithm (a) Input image (Kidney stone image) (b) Classification result of parallel piped classifier (c) Classification result of bayesian classifier.

Figure 2 represents bar graph comparison between parallel piped classifier and bayesian classifiers. The X-Axis represents the two classifiers used to classify kidney stone detection and Y-Axis represents the performance measure mean accuracy of both techniques with ($\pm$ 2 SD) with 95% CI. The comparison of parallel piped technique and bayesian classifier based on classification accuracy reflects the anticipated yield. In addition, t-test results show up to be a factually inconsequential contrast in exactness between two strategies. These discoveries have shown that parallel piped can be foreseen more rapidly than the bayesian classifier technique.

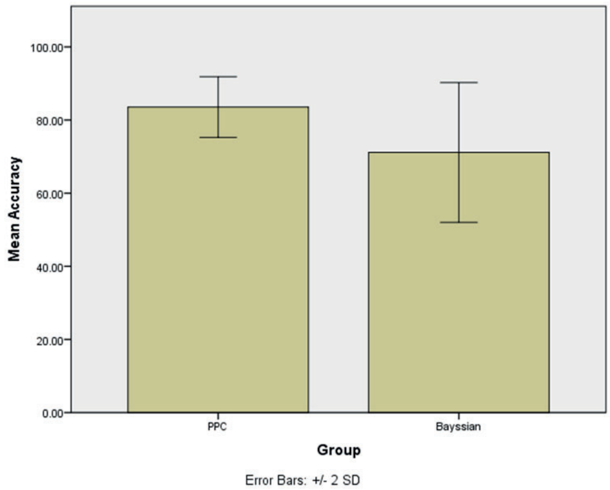

Fig. 2. Bar chart representation of the comparison between parallel piped classifier and bayesian classifiers.The X-Axis represents the two classifiers used to classify kidney stone detection and Y-Axis represents the mean accuracy of both techniques with (+ 2 SD) with 95% CI

DISCUSSION

In this research paper, the parallel piped classifier (83.5410%) outperformed in terms of accuracy for detecting kidney stones than bayesian classifier (71.1314%). Many researchers have proposed a model based on ensemble techniques using a parallelepiped classifier, with the purpose of assessing the model's accuracy, precision. With a precision of 98 percent and an accuracy of 54 percent, the findings were accomplished in (Eliza and K. 2019). Another investigation developed a computer-aided identification approach based on the classifiers. Logistic regression and parallelepiped classifier (Hassanien and Oliva 2017) have been used in feature selection and a principal component analysis model has been used to correctly detect the stone with an accuracy of 90%. Actual (Class 1) and Actual (Class 2) selections can be reduced using different classifiers (Patgiri and Ganguly 2021). The experimental outcomes revealed that SVM-PCA had the highest accuracy of 98.9 percent over the parallel piped classifier.

The proposed strategy, in combination with the suggested classification algorithms, could soon be beneficial in the detection of kidney stones. For kidney stone image classification, parallel piped, bayesian classifiers and other classifiers have greater accuracy and should be updated and improved (Patgiri and Ganguly 2021). In future, the algorithms have been enhanced so that they can easily use it on detection of kidney stones at an early stage. Furthermore, the study might be broadened to early prediction by collecting data from a number of sites around the world and generating a more precise and common, discriminating model.

CONCLUSION

Parallel piped classifier and bayesian classifiers were used to detect kidney stones. Parallel piped classifier outperforms bayesian classifiers in terms of classification accuracy for the detection of kidney stones using Matlab programming. This research can be used to predict kidney stone detection in clinical settings such as hospitals and testing centers.

DECLARATION

Conflict of Interests

No conflict of interest in this manuscript.

Authors Contribution

Author UK was involved in data collection, data analysis, and manuscript writing. Author RR was involved in conceptualization, data validation, and critical review of manuscript.

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