

Automated detection of chronic kidney disease using higher-order features and elongated quinary patterns from B-mode ultrasound images

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	<p>vector machine and a radial basis function, utilizing only 5 features, and resulting in an accuracy of 99.75%, and a sensitivity and specificity of 100% and 99.57%, respectively. Based upon these findings, it is evident that the technique accurately and automatically identifies subjects with and without CKD from B-mode ultrasound images.</p>
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Automated Detection of Chronic Kidney Disease Using Higher Order Features and Elongated Quinary Patterns From B-Mode Ultrasound Images

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Abstract

Chronic kidney disease (CKD) is a continuing loss of kidney function, and early detection of this disease is fundamental to halt its progression to end-stage disease. Numerous methods have been proposed to detect CKD, mainly focusing on classification based upon peripheral clinical parameters, quantitative ultrasound parameters that must be manually calculated, or on shear wave elastography. No studies have been found that detect the presence or absence of CKD based solely from one B-mode ultrasound image. In this work, we propose an automated system to detect chronic kidney disease utilizing only the automatic extraction of features from a B-mode ultrasound image of the kidney, with a database of 405 images. Higher order bispectrum and cumulants, and elongated quinary patterns, are extracted from each image to provide a final total of 24,480 features per image. These features were subjected to a locality sensitive discriminant analysis (LSDA) technique, which provides 30 LSDA coefficients. The

coefficients were arranged according to their t-value and inserted into various classifiers, to yield the best diagnostic accuracy using the least number of features. The best performance was obtained using a support vector machine and a radial basis function, utilizing only 5 features, and resulting in an accuracy of 99.75%, and a sensitivity and specificity of 100% and 99.57%, respectively. Based upon these findings, it is evident that the technique accurately and automatically identifies subjects with and without CKD from B-mode ultrasound images.

Keywords: chronic kidney disease, bispectrum, cumulants, elongated quinary pattern, locality sensitive discriminant analysis, ultrasound

1. Introduction

Chronic kidney disease (CKD) is a progressive loss of kidney function of at least three months' duration, whose main causes are primary renal disorder, diabetes, and hypertension. Regardless of the aetiology, CKD is defined by renal fibrosis, and is characterised by glomerulosclerosis and tubulointerstitial fibrosis [1]. As CKD progresses, it results in an extensive tissue scarring, which causes the impairment of normal kidney parenchyma. **Figure 1** shows an illustration of a healthy and diseased CKD. The pathologic damage is irreversible and can lead to morbidity and mortality . The prevalence of CKD is increasing worldwide. The estimated prevalence of CKD in the U.S. was 16.8% in 2007, while in Asia the prevalence ranged from 12.1% to 17.5% (2009-2010) [2]. Hence, the early intervention of CKD is crucial so that appropriate treatments can be administered to reduce the development of end-stage disease, which is costly and difficult to manage.

In CKD, impairment of kidney morphology and function are closely related. As such, information on morphology and function are required for CKD diagnosis. Currently, the role of laboratory testing is to provide a surrogate marker to estimate renal function, which is

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58 measured using the glomerular filtration rate (GFR). CKD is grouped into 5 severity-based
59 stages according to the GFR, and presence of CKD is defined by a GFR of less than 60mL/min
60 per 1.73 m². When the GFR is calculated from serum creatinine values, it is known as the
61 estimated GFR (eGFR), which incorporates one of several formulas, such as MDRD eGFR,
62 CKD-epi eGFR and Cockcroft-Gault Creatinine Clearance. Imaging predominantly provides
63 structural information. Non-invasive imaging by ultrasound, magnetic resonance imaging
64 (MRI), and computed tomography (CT) are helpful to reveal kidney morphology. These
65 imaging modalities enable satisfactory visualization and evaluation of the urinary tract and
66 extra renal pathologies affecting the kidneys. As such, other potential causes of CKD, such as
67 urinary tract obstruction, can readily be identified. However, CT and MRI imaging present
68 their own risks and downsides, including radiation exposure and potential renal damage from
69 the administration of iodinated contrast medium in the case of CT scans, being expensive to
70 perform, and in the case of MRI, having limited patient selection due to certain
71 contraindications. Therefore, CT and MRI imaging, while informative in specific situations,
72 are not commonly used in CKD diagnosis [3].

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73 Renal ultrasound is considered as the imaging modality of choice for the evaluation of
74 subjects with previously undiagnosed kidney dysfunction, due to its being radiation-free, the
75 ease of imaging the kidney and of alterations of image aspect due to disease, and its low
76 associated cost. Furthermore, kidney disease often results in smaller kidneys that have a higher
77 echogenicity, making it possible to differentiate between those with acute kidney injury [1].
78 Parenchymal echogenicity is also a widely used marker to detect nephropathy. It is assessed by
79 comparing the echogenicity of the kidney cortex with that of the adjacent liver or spleen
80 echogenicity [4]. Some other important features that can be appreciated with B-mode
81 ultrasound images of the kidney are the differentiation between intrinsic causes of kidney

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3 82 disease and obstructive disease, and the identification of congenital or hereditary kidney
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5 83 disease.

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7 84 Numerous studies have investigated the research topic concerning the correct prediction
8 85 of CKD using advanced classification algorithms, but utilized other clinical variables extracted
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10 86 from the patient data, such as age, sex, weight, blood pressure, and creatinine, in order to predict
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12 87 the GFR values [5]. Other studies have focused upon quantitative ultrasound imaging and
13
14 88 calculated parameters such as kidney length, cortical thickness, pixel intensity, and intrarenal
15
16 89 artery peak systolic velocity, and have evaluated the differences in these parameters among
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18 90 mild, moderate and severe CKD [6]. Still other approaches focused instead on shear wave
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20 91 elastography to evaluate renal parenchymal stiffness [7], [8]. These investigations, however,
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22 92 either require substantial clinical data that may not always be available, they may require
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24 93 several ultrasound clinical parameters that must be calculated and reported manually, or they
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26 94 may require specific ultrasound devices that permit shear wave elastography analysis. It is
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28 95 therefore evident that there is a need for an automated system for correct prediction of CKD,
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30 96 using data that is readily collected and does not require manual intervention.
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38 97 In this study, we present a completely automated system that classifies the presence or
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40 98 absence of chronic kidney disease based only upon the B-mode kidney ultrasound image. To
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42 99 date, this is the first work that presents CKD prediction based solely upon a single B-mode
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44 100 ultrasound image.
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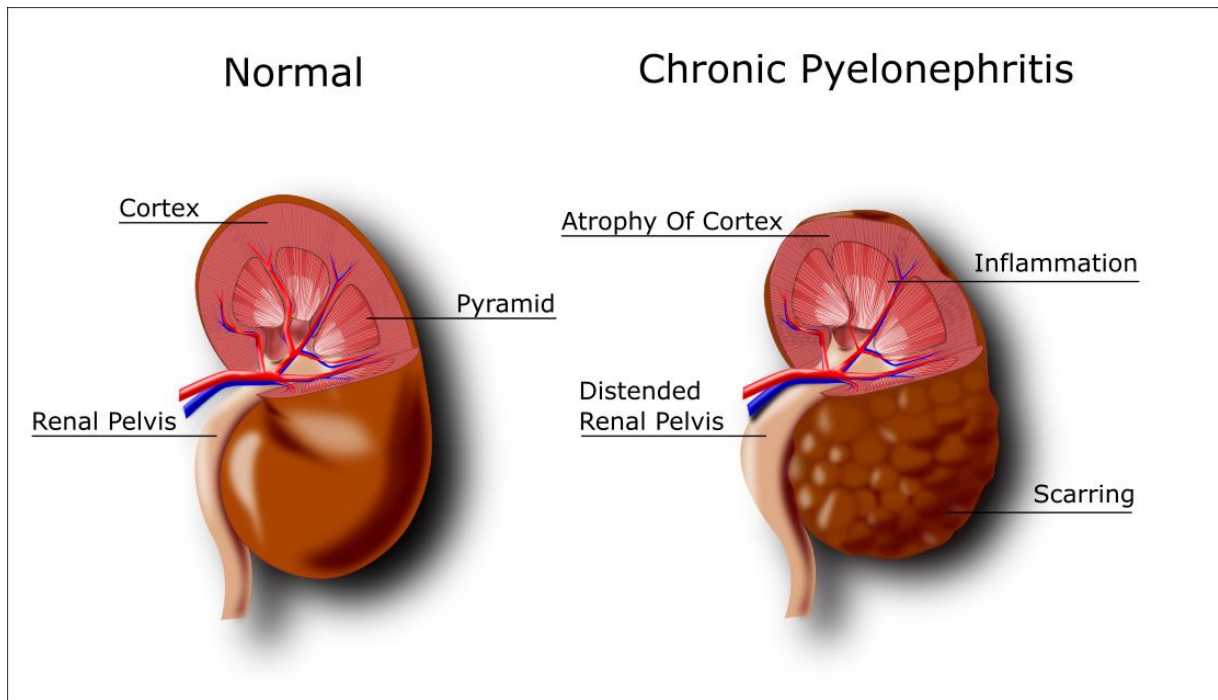


Figure 1. An illustration of the anatomy of a healthy and diseased kidney.

2. Materials and methods

In this section, each step of the developed system is described in-depth, as summarized in

Figure 2.

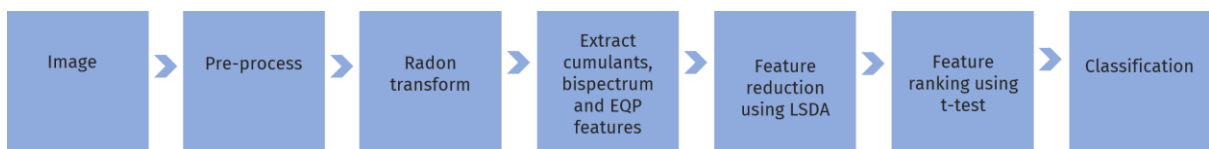


Figure 2. The algorithm of the proposed technique.

2.1 Database

In this study, a total of $N = 405$ subjects was considered to validate the proposed system for diagnosis of chronic kidney disease from ultrasound images. 174 subjects were chronic kidney disease patients, whereas the remaining 231 subjects did not present any kidney disease. The images were acquired at the renal cortex, without the renal medulla and sinus, using an

118 ultrasound system. Local medical ethics approval was obtained from the Institutional Ethics
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3 119 Committee. The presence of chronic kidney disease was confirmed by the nephrologist. The
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5 120 1st row of **Figure 3** displays an example of a kidney ultrasound image for a subject with chronic
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7 121 kidney disease, versus a normal subject.
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10 122 **2.2 Preprocessing and Radon transform**

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13 123 As a first step, the ultrasound images are resized to a standard dimension of 512×512
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16 124 pixels, and are then converted to grayscale. Next, an adaptive histogram equalization process
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18 125 was applied to the image [9] in order to enhance its visibility level. This was done by using
19
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21 126 local regions, termed tiles, within which the contrast is adaptively enhanced.
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24 127 After this first preprocessing stage, the Radon transform (RT) was calculated. The RT
25
26 128 performs image projection operations on the image, where the two-dimensional RT is the
27
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29 129 projection of the image intensity along a radial line that is oriented at a specific angle,
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31
32 130 generating a line integral which is the sum of the pixel intensities in each considered direction
33
34 131 [10]. The RT can therefore capture directional features of an image and preserve intensity
35
36 132 variations, preserving and boosting spatial-frequency information in the image. The RT was
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39 133 calculated every 2° from 0° to 178° , thereby providing 90 different angles, and therefore 90
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41 134 different 1D RT sinogram signals.
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44 135 **2.3 Feature extraction**

45 46 47 136 *2.3.1 Bispectrum and cumulants*

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50 137 From the 1D RT sinogram signals (one signal for each considered angle), the higher-order
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53 138 bispectrum and cumulant features were extracted.
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139 The spectral representations of higher order moments of a signal are known as higher order
 140 spectra [11], and the 3rd order statistic is known as the “bispectrum” , $B(x_1, x_2)$, or the Fourier
 141 transform of the 3rd order correlation, given by the averaged biperiodogram:

$$B(x_1, x_2) = E[F(x_1)F(x_2)F^*(x_1 + x_2)]$$

(1)

144 where $F(x)$ is the Fourier transform of the signal, * is the complex conjugation operator
 145 and $E[.]$ is the expectation operator, the average over a group of realizations of the random
 146 signal. Hence, the bispectrum is a function of two frequencies and exhibits symmetry (second
 147 row of **Figure 3**), being that the bispectrum of a real-valued signal is defined uniquely within
 148 the triangle $0 \leq x_2 \leq x_1 \leq x_1 + x_2 \leq 1$, assuming no bispectral aliasing [12].

149 Cumulants are higher-order statistics that have been substantially used in the biosignal
 150 processing field, given that first and second-order statistics are insufficient for representing
 151 nonlinear signals [13].

152 Thus, the first four order moments (m_n^F) can be calculated as follows:

$$m_1^F = E[F(n)]$$

$$m_2^F(i) = E[F(n)F(n + i)]$$

$$m_3^F(i, j) = E[F(n)F(n + i)F(n + j)]$$

$$m_4^F(i, j, k) = E[F(n)F(n + i)F(n + j)F(n + k)]$$

(2)

158 where $F(n)$ is assumed to be a zero-mean process. From these moments, it is therefore possible
 159 to compute the cumulants (C_n^F) as nonlinear combinations (3rd row of **Figure 3**). Here the first
 160 four order cumulants are defined:

$$\begin{aligned}
161 \quad C_1^F &= m_1^F \\
162 \quad C_2^F(i) &= m_2^F(i) \\
163 \quad C_3^F(i, j) &= m_3^F(i, j) \\
164 \quad C_4^F(i, j, k) &= m_4^F(i, j, k) - m_2^F(i)m_2^F(j - k) - m_2^F(k - i) - m_2^F(k)m_2^F(i - j) \\
165 & \tag{3}
\end{aligned}$$

166 The bispectrum and cumulants obtained from the 1D sinogram are each described using 136
167 features; thus considering 90 different angles, each image is therefore represented with 12,240
168 bispectrum features and 12,240 cumulant features.

169 *2.3.1 Elongated quinary pattern*

170 Starting from the 2D RT image, we then applied an elongated quinary pattern (EQP)
171 quantization technique using five levels of encoding [14]. In order to obtain elongated quinary
172 patterns, the input image first undergoes a process in which the left-right (LR) and XY gradient
173 magnitudes and angles are computed. To do so, gradient components are extracted using Sobel
174 kernels in various orientations, and are then combined [15]. Therefore, for each image, one
175 angle image (4th row of **Figure 3**) and one magnitude image (5th row of **Figure 3**) is calculated.
176 Each of these images is represented by 8 coefficients (4 phase angles and 4 magnitudes – 2 XY
177 directions and 2 LR directions). Numerous features were then derived from the magnitude and
178 angle images. Specifically, the fuzzy entropy (Ef) [16], Kapur's entropy (Ek) [17], max entropy
179 (Emax), Renyi's entropy (Er) [18], Shannon's entropy (ESh) [19], Vajda Entropy (Ev) [20] and
180 Yager's entropy (Ey) [21] were extracted, and then the bispectrum entropies represented by
181 five features were computed at every 1 degree.

182 Therefore, a total of 14,512 features were calculated based upon the elongated quinary
183 pattern images. One hundred and twelve of these features were computed by considering the 8

184 EQP coefficients and the 7 entropies listed above, whereas the remaining 14,400 features were
185 computed with the bispectrum entropies, from 5 features and 180 different angles.

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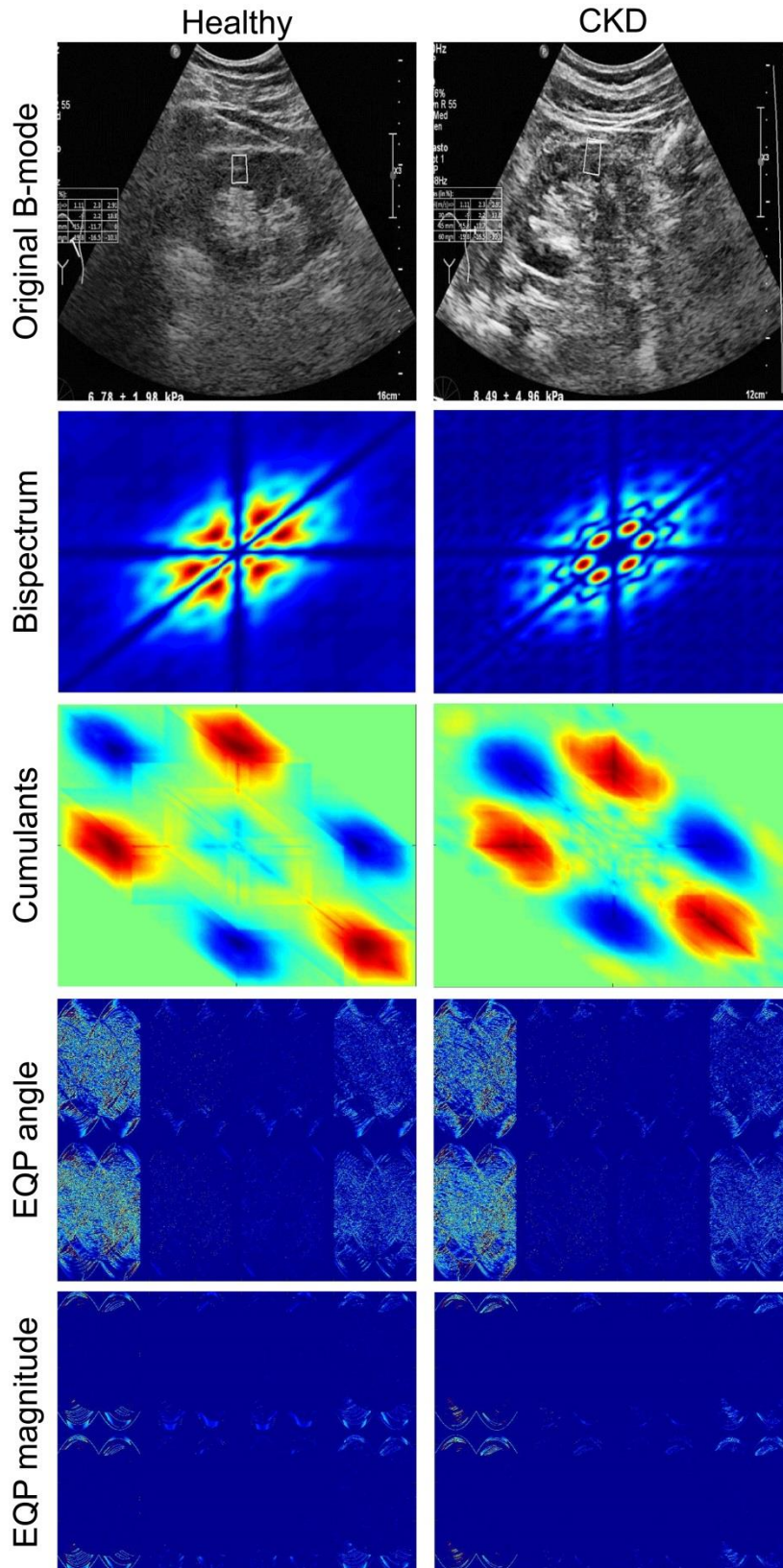


Figure 3. Example of system image processing, showing results obtained with healthy and diseased images (first and second columns, respectively). First row: Original B-mode ultrasound images of the kidney; second row: bispectrum images; third row: cumulants images; fourth row: EQP angle images; fifth row: EQP magnitude images.

2.4 Feature reduction and classification

193 Given that each image is over-represented with a total of 24,480 features, a feature
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2 194 reduction algorithm was then applied to reduce the number of image features. Specifically, a
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4 195 locality sensitive discriminant analysis (LSDA) approach was employed. The LSDA technique
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7 196 has been found helpful to study the relationship between data points; it is known to preserve
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9 197 both discriminant and local geometrical structure [22], and has recently been shown to be
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11 198 highly effective in medical image analysis [23]. For a detailed description of the functionality
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14 199 of the LSDA method, please refer to Cai et al. [22].
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17 200 After the application of the LSDA feature reduction technique, a total of 30 features
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19 201 remained, which were then ranked based upon the statistical t-test, thereby providing 9
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22 202 significant features.
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25 203 The following methods were then employed to enable automated classification from the
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27 204 two-class system: k-nearest neighbour (k-NN), quadratic discriminant analysis (QDA), linear
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29 205 discriminant analysis (LDA), decision tree (DT), probabilistic neural network (PNN), and
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31 206 support vector machine (SVM). The SVM classifier can be employed using different kernel
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33 207 functions, and here we implemented both polynomial functions (i.e., polynomials 1, 2 and 3)
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35 208 and a radial basis function (RBF) [24]. For a more detailed description of these classification
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38 209 techniques, please refer to Acharya et al. [23].
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43 210 A ten-fold cross validation strategy was utilized to train and validate the proposed algorithm.
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45 211 To evaluate and assess performance, the following system parameters were calculated: the
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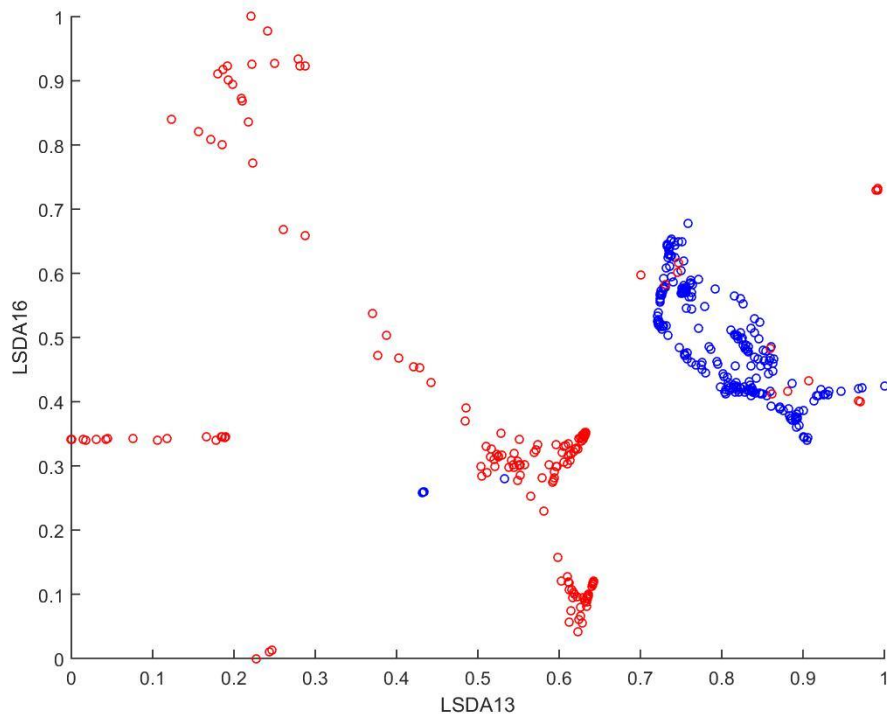
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216 **3. Results**

217 **3.1 Feature extraction results**

218 As mentioned previously, each subject is over-represented with a total of 24,480 features
219 obtained from each image. Hence, the LSDA technique was employed to reduce 24,480
220 features to 30 LSDA coefficients. The LSDA coefficients were then positioned according to
221 significance. **Table 1** showcases the results of the highly ranked LSDA coefficients. **Figure 4**
222 displays a scatterplot of the two most significant LSDA coefficients, which illustrate how these
223 features can be clearly separated, and therefore provide a satisfactory classification accuracy,
224 which will subsequently be discussed. The results portrayed both in **Figure 4** and in **Table 1**
225 show how the LSDA coefficients, extracted from the set of features, exhibit a clear distinction
226 between subjects with and without CKD.



227 **Figure 4. Scatter plot of the first and second most significant LSDA coefficients.**

230

231 **Table 1. Results obtained after feature reduction using LSDA.**

LSDA coefficient	Normal		CKD		p-value	t-value
	Mean	SD	Mean	SD		
LSDA13	-5.91x10 ¹⁴	1.84x10 ¹⁴	-1.29x10 ¹⁵	5.16x10 ¹⁴	0.0000*	19.0087
LSDA16	4.15x10 ¹⁵	1.84x10 ¹⁴	3.88x10 ¹⁵	5.10x10 ¹⁴	0.0000*	7.3134
LSDA14	2.12x10 ¹⁵	1.18x10 ¹⁴	2.31x10 ¹⁵	6.54x10 ¹⁴	0.0000*	4.3864
LSDA12	-9.49x10 ¹⁴	4.80x10 ¹³	-7.78x10 ¹⁴	6.59x10 ¹⁴	0.0001*	3.9215
LSDA10	3.32x10 ¹⁴	6.26x10 ¹⁴	5.07x10 ¹⁴	1.51x10 ¹⁴	0.0004*	3.5951
LSDA9	-9.03x10 ¹⁴	6.80x10 ¹³	-1.04x10 ¹⁵	7.60x10 ¹⁴	0.0070*	2.7122
LSDA15	-6.62x10 ¹⁵	6.51x10 ¹³	-6.53x10 ¹⁵	5.82x10 ¹⁴	0.0193*	2.3488
LSDA4	-5.61x10 ¹⁵	4.65x10 ¹⁴	-5.53x10 ¹⁵	2.62x10 ¹⁴	0.0307*	2.1684
LSDA11	-9.29x10 ¹⁴	5.40x10 ¹³	-1.00x10 ¹⁵	5.42x10 ¹⁴	0.0422*	2.0383
LSDA8	-3.53x10 ¹⁵	2.19x10 ¹⁴	-3.61x10 ¹⁵	5.94x10 ¹⁴	0.0542	1.9311
LSDA19	-3.96x10 ¹⁵	2.83x10 ¹⁴	-4.04x10 ¹⁵	5.94x10 ¹⁴	0.0686	1.8263
LSDA3	-1.71x10 ¹⁵	3.78x10 ¹³	-1.78x10 ¹⁵	7.47x10 ¹⁴	0.1332	1.5048
LSDA1	-7.19x10 ¹⁵	2.00x10 ¹³	-7.23x10 ¹⁵	6.01x10 ¹⁴	0.2995	1.0388
LSDA18	1.22x10 ¹⁵	1.94x10 ¹⁴	1.19x10 ¹⁵	5.81x10 ¹⁴	0.4177	0.8112
LSDA2	-1.22x10 ¹⁶	1.96x10 ¹³	-1.21x10 ¹⁶	6.08x10 ¹⁴	0.5251	0.6361
LSDA23	9.06x10 ¹⁴	5.10x10 ¹⁴	9.36x10 ¹⁴	5.53x10 ¹⁴	0.5674	0.5723
LSDA26	5.48x10 ¹⁵	2.58x10 ¹⁴	5.50x10 ¹⁵	6.04x10 ¹⁴	0.7754	0.2855
LSDA5	4.22x10 ¹⁵	1.05x10 ¹⁴	4.21x10 ¹⁵	5.94x10 ¹⁴	0.7812	0.2780
LSDA17	-3.77x10 ¹⁵	1.58x10 ¹⁴	-3.76x10 ¹⁵	6.58x10 ¹⁴	0.7930	0.2626
LSDA27	3.93x10 ¹⁵	3.59x10 ¹⁴	3.94x10 ¹⁵	5.92x10 ¹⁴	0.8109	0.2394
LSDA20	5.69x10 ¹⁴	4.86x10 ¹⁴	5.64x10 ¹⁴	5.64x10 ¹⁴	0.9139	0.1082
LSDA28	2.52x10 ¹⁵	4.80x10 ¹⁴	2.51x10 ¹⁵	2.10x10 ¹⁴	0.9189	0.1019
LSDA22	7.05x10 ¹⁵	5.16x10 ¹⁴	7.05x10 ¹⁵	3.40x10 ¹⁴	0.9214	0.0987
LSDA30	1.09x10 ¹⁴	3.32x10 ¹⁴	1.05x10 ¹⁴	5.08x10 ¹⁴	0.9313	0.0863
LSDA25	-1.19x10 ¹⁶	4.40x10 ¹⁴	-1.19x10 ¹⁶	4.05x10 ¹⁴	0.9317	0.0857
LSDA21	1.61x10 ¹⁵	3.50x10 ¹⁴	1.61x10 ¹⁵	5.24x10 ¹⁴	0.9581	0.0526
LSDA24	-2.49x10 ¹⁵	3.87x10 ¹⁴	-2.48x10 ¹⁵	5.07x10 ¹⁴	0.9740	0.0326
LSDA7	4.31x10 ¹⁵	1.97x10 ¹³	4.31x10 ¹⁵	7.08x10 ¹⁴	0.9759	0.0302
LSDA6	2.42x10 ¹⁵	1.81x10 ¹³	2.42x10 ¹⁵	6.50x10 ¹⁴	0.9844	0.0195
LSDA29	4.81x10 ¹⁵	2.17x10 ¹⁴	4.81x10 ¹⁵	6.12x10 ¹⁴	0.9858	0.0178

232 *statistically significant features; LSDA: locality sensitive discriminant analysis; SD: standard deviation; CKD:
 233 chronic kidney disease.

236 **3.2 Classification results**

237 The final ranked features are then subject to classification using DT, LDA, QDA, k-NN,
 238 PNN, and SVM using polynomial and RBF kernel functions. The classifiers were employed
 239 singly to achieve the best classification using the least number of features. The classification

240 results, in terms of the confusion matrix, accuracy, positive predictive value, sensitivity, and
 241 specificity, are given in [Table 2](#). As can be noted, the SVM using the radial basis function
 242 provided the best results with only 5 features, having an accuracy of 99.75%, a PPV equal to
 243 99.43%, a sensitivity of 100%, and a specificity of 99.57%. These results demonstrate how the
 244 developed system was able to correctly diagnose the presence of chronic kidney disease, and
 245 only wrongly classified a normal subject as a diseased subject in 0.43% of the cases (one image
 246 was wrongly classified as a false positive).

Table 2. Classification results for chronic kidney disease determination

Classifier	N° feat.	TP	TN	FP	FN	Acc. (%)	PPV (%)	Sens. (%)	Spec. (%)
DT	8	174	228	3	0	99.26	98.31	100.00	98.70
LDA	8	167	231	0	7	98.27	100.00	95.98	100.00
QDA	5	167	224	7	7	96.54	95.98	95.98	96.97
SVM Poly 1	5	167	230	1	7	98.02	99.40	95.98	99.57
SVM Poly 2	8	171	231	0	3	99.26	100.00	98.28	100.00
SVM Poly 3	5	174	230	1	0	99.75	99.43	100.00	99.57
k-NN	4	165	227	4	9	96.79	97.63	94.83	98.27
PNN	5	171	230	1	3	99.01	99.42	98.28	99.57
SVM RBF	5	174	230	1	0	99.75	99.43	100.00	99.57

feat: features; TP: true positives; TN: true negatives; FP: false positives; FN: false negatives; Acc: accuracy; PPV: positive predictive value; Sens: sensitivity; Spec: specificity.

4. Discussion

In this study, we used a database of 405 images to develop and evaluate the performance of an automated system for distinguishing subjects with or without CKD, based upon B-mode ultrasound kidney imaging. Numerous features were extracted from each image, and the number of features was then reduced using the LSDA technique. We showed how the remaining 30 LSDA coefficients, and specifically the first five when ranked using *t-values*, were suitable and capable of automatically detecting the presence or absence of CKD. Based upon [Figure 3](#), it can be observed that the bispectrum and cumulant plots of healthy and CKD

261 ultrasound images are unique. Furthermore, the EQP images (angle and magnitude) show that
262 the healthy image displays more patterns as compared to the CKD image. Thus, a high
263 classification performance of 99.75% was obtained with the proposed feature extraction
264 techniques.

265 Additionally, the incidence of CKD has recently increased, and to remedy the
266 concomitant financial strain, efforts to reduce the cost of managing the disease, as well as
267 accurate CKD classification, are essential. The gold standard for the determination of CKD is
268 the GFR/eGFR, in which CKD is categorized into 5 severity-based stages. Nearly 50 formulas
269 have been developed to estimate the GFR since 1957 [8]. Studies have also shown that the
270 average error of eGFR was $\pm 30\%$ of the GFR [25]. In a patient with a GFR of 50 mL/ min,
271 eGFR could vary from 35 to 65 mL/min, thereby crossing the threshold of what would define
272 normal and abnormal GFR [26]–[28]. Regarding imaging studies, renal echogenicity can be
273 used for evaluating the kidney, as described in the Introduction. There are four different grades
274 of renal echogenicity, from 0 to III. However, renal damage cannot be excluded in a patient
275 with an echogenicity grade 0 or grade I. In the assessment of kidney pathologies, the sensitivity
276 and specificity of echogenicity grade I and grade II in detecting renal disease are 62% and 58%,
277 respectively, while the sensitivity and specificity of echogenicity grade III are 20% and 96%,
278 respectively [4]. These show that ultrasound kidney analysis has low sensitivity and specificity
279 in the detection of renal damage [29, 30]. Hence, a solid and highly accurate method to
280 determine the presence of CKD is of vital advantage for clinicians.

281 As mentioned in the Introduction, numerous prior investigations have focused on the
282 correct detection of CKD. However, the majority of these studies either implemented advanced
283 classification techniques on other clinical data obtained from each patient [5], [31]–[34], or
284 they calculated quantitative ultrasound parameters to detect differences between healthy
285 subjects and subjects with varying severity of CKD [6]. To the present time, no published

286 studies use only one B-mode ultrasound image to determine the presence or absence of CKD,
287 an approach that can ease clinician workload, since it is necessary to acquire only a single B-
288 mode ultrasound image for a screening test, and since it does not necessitate the collection of
289 further clinical information.

290 The advantages of the method that we propose herein are therefore as follows:

- 291 • An automated classification of the presence or absence of CKD without using
292 image segmentation techniques;
- 293 • The higher order features and EQP are able to distinguish minute variations in
294 ultrasound images;
- 295 • High accuracy, sensitivity, and specificity. Specifically, an accuracy of 99.75%,
296 a specificity 99.57%, and a sensitivity of 100% was determined. Therefore, no
297 CKD subjects were incorrectly classified as healthy, and only one healthy
298 subject was classified as having disease;
- 299 • The system is completely automated, it requires no user interaction, and only
300 one B-mode ultrasound image is needed.

301 *Limitations and future directions*

302 The limitation of our work is that the database size contained only 405 subjects for
303 evaluation. It would be necessary to test the developed technique on a larger database for
304 applicability and diversity purposes. As a result, we did not yet render a state-of-the-art
305 technique in this study. Nevertheless, we will develop an automated diagnostic system with
306 deep learning in our next work. Deep learning is a highly regarded approach of artificial
307 intelligence that eradicates the process of features extraction, selection of features, and
308 classification. The architecture of deep learning enables the network to incorporate the
309 conventional processes into one model [35]. It has been employed in diverse areas, from object

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310 recognition [36] and damage assessment of high-rise building structures [37], to medical
311 imaging [38]-[40] and physiological signals [41]-[43]. The convolutional neural network
312 (CNN) is the most common form of deep learning [44]. The CNN paradigm entails a sequence
313 of convolution, pooling, and fully-connected layering. Firstly, the input image is convolved
314 with a defined kernel to produce a feature map. Through the convolution process, it singles out
315 the characteristic features from the input. Thereafter, the pooling layer is implemented. It aims
316 to manage overfitting of the model. Lastly, the fully-connected layer is the final output layer
317 where class membership is determined.

318 In future work, we plan to design a CNN architecture with a greater number of
319 ultrasound images (healthy and diseased) collected for study.

320

321 **5. Conclusions**

322 In this work, a novel approach using higher-order features and elongated quinary patterns,
323 combined with the LSDA feature reduction technique, was proposed to automatically identify
324 subjects with and without CKD using B-mode ultrasound images. Application of the developed
325 technique resulted in an accuracy of 99.75%, a 99.43% PPV, 100% sensitivity, and 99.57%
326 specificity with the SVM classifier and 5 features utilized. Importantly, the system exhibited
327 excellent sensitivity, never incorrectly classifying a diseased subject as a healthy one. To the
328 best of our knowledge, this is the first system that can automatically detect the presence or
329 absence of CKD from ultrasound B-mode images requiring no user interaction, and can be used
330 as a diagnostic and screening tool. Future work to be done includes enlarging the image
331 database, further testing of the developed system, and the determination not only of the
332 presence of CKD but also the severity of the disease.

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