ARAŞTIRMA MAKALESİ / *RESEARCH ARTICLE*

Computer-Based Characterization of Specific Cystic Renal Masses of Bosniac Classification with Traditional Machine Learning and Modified Deep Learning Methods

Geleneksel Makine Öğrenme ve Özelleştirilmiş Derin Öğrenme Yöntemleri ile Bosniak Sınıflandırmasına Ait Özel Kistik Böbrek Kitlelerinin Bilgisayar Tabanlı Karakterizasyonu

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ABSTRACT

Aim: *This study aims to develop a novel artificial intelligence-based pre-diagnosis system for classifying cystic renal masses (CRM) according to the Bosniak classification. The objective is to distinguish between the five diagnostic stages of the Bosniak classification using traditional machine learning (ML) and deep learning (DL) techniques.*

Material and Method: *A total of 20 contrast-enhanced CT images were collected for each of the five Bosniak stages (I, II, IIF, III, IV), verified by a uro-oncologist and radiologist. Additional image variations were generated using the Keras image processing library during the data augmentation phase, resulting in 600 images per stage. This process included operations such as brightness and contrast modification, image rotation, noise addition, and flipping. These augmented images were then used to train both ML and DL models. The k-Nearest Neighbors (kNN) algorithm was applied for the ML approach, while modified Convolutional Neural Networks (CNN) and VGG-16 models were used for the DL approach. Model performances were evaluated using receiver operating characteristic (ROC) analysis and area under the curve (AUC) metrics.*

Results: *The kNN algorithm accurately classified the Bosniak stages with an AUC of 0.854. The VGG-16 model demonstrated superior performance, with an AUC of 0.978, achieving higher classification accuracy than the kNN model.*

Conclusion: *The computerized Bosniak classification system based on CT images effectively differentiates between the five Bosniak stages. This system, utilizing both ML and DL models, has the potential to enhance the pre-diagnosis of CRM in clinical settings and can also effectively exclude other types of renal masses.*

Key words: *renal mass; Bosniak classification; machine learning; feature extraction; deep learning*

ÖZET

Amaç: *Bu çalışma, Bosniak sınıflamasına göre kistik renal kitleleri sınıflandıran yapay zeka tabanlı yeni bir ön tanı sistemi geliştirmeyi amaçlamaktadır. Amacımız, Bosniak sınıflamasındaki beş tanısal aşamayı (I, II, IIF, III, IV) geleneksel makine öğrenimi (ML) ve derin öğrenme (DL) teknikleri kullanarak ayırt etmektir.*

Materyal – Metod: *Her bir Bosniak aşaması (I, II, IIF, III, IV) için üro-onkolog ve radyolog tarafından doğrulanmış toplam 20 kontrastlı BT görüntüsü toplandı. Veri çoğaltma aşamasında, Keras görüntü işleme kütüphanesi kullanılarak ek görüntü varyasyonları üretildi ve her aşama için 600 görüntü elde edildi. Bu süreçte parlaklık ve kontrast ayarı, görüntü döndürme, gürültü ekleme ve çevirme gibi işlemler yapıldı. Bu çoğaltılmış görüntüler, hem Makine Öğrenmesi hem de DÖ modellerinin eğitiminde kullanıldı. Makine Öğrenmesi yaklaşımı için k-En Yakın Komşu (kNN) algoritması uygulanırken, Derin Öğrenme yaklaşımı için değiştirilmiş Konvolüsyonel Sinir Ağları (KSA) ve VGG-16 modelleri kullanıldı. Model performansları, ROC (alıcı işletim karakteristiği) analizi ve eğri altındaki alan (EAA) metrikleri ile değerlendirildi.*

Bulgular: *kNN algoritması, Bosniak tiplerini doğru sınıflandırmada 0.854 AUC değerine ulaştı. Karşılaştırmalı olarak, VGG-16 modeli 0.978 AUC ile üstün performans gösterdi ve kNN modelinden daha yüksek sınıflandırma doğruluğu sağladı.*

Sonuç: *BT görüntüleri baz alınarak geliştirilen bilgisayarlı Bosniak sınıflama sistemi, Bosniak aşamaları arasında etkili bir şekilde ayrım yapmaktadır. Makine Öğrenmesi ve DÖ modellerini kullanan bu sistem, klinik ortamlarda kistik renal kitlelerin ön tanısını geliştirme potansiyeline sahip olup, diğer böbrek kitleleri türlerini dışlamak için de etkili olabilir.*

Anahtar kelimeler: *renal kitle; Bosniak sınıflaması; Makine Öğrenmesi; özellik çıkarımı; derin öğrenme*

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Introduction

Cystic renal lesions are fluid-filled sacs in the kidneys and are formations that exhibit a wide range of different characteristics[1]. According to research, the incidence of cystic renal lesions in individuals over the age of 50 can be as high as 50%. The incidence of these lesions increases with age, and they are generally benign[2]. However, careful evaluation is necessary because some cystic renal lesions may have malignant potential[3].

The basic methods used to diagnose cystic renal lesions include ultrasonography, computed tomography (CT), and magnetic resonance imaging (MRI)[4]. Ultrasonography is a widely used, non-invasive, and low-cost method. However, when detailed evaluation of the internal structure and septa of the lesions is required, advanced imaging methods such as CT and MRI should be used[5]. These methods are more effective in determining whether the lesions contain solid components, whether there is calcification, and whether wall thickness[6].

The most common classification system used to evaluate cystic renal lesions is Bosniak staging[7]. Bosniak classification helps determine the risk of malignancy based on the radiological features of the lesions. Bosniak stage I and II lesions are generally considered benign, while Bosniak stage III and IV lesions have a higher risk of malignancy[8]. Therefore, Bosniak III and IV lesions may require surgical excision or close follow-up. However, Bosniak stage IIF presents a more complex picture[9]. Lesions in this stage are between Bosniak II and III and usually require observation[10]. Although the malignant potential of these lesions is low, regular follow-up is recommended when a definitive distinction cannot be made. The Bosniak IIF classification is a crucial category within the Bosniak classification system, which is used to assess renal cysts based on their imaging characteristics in CT scans. Bosniak IIF specifically pertains to complex cysts that demonstrate some atypical features, such as a few thin septa or a slightly increased attenuation, which suggests the potential for benign but atypical behavior.

Traditional evaluation of these cysts often relies on the subjective interpretation of radiologists, which can lead to inconsistencies in diagnosis. However, integrating image processing and deep learning techniques presents a transformative approach to enhance diagnostic accuracy. By utilizing convolutional neural networks (CNNs), these advanced technologies can automatically analyze imaging data, extracting relevant features and patterns that may be imperceptible to the human eye. Training deep learning models on large, annotated datasets allows for the development of robust algorithms to distinguish between Bosniak II and IIF cysts with high precision. Image preprocessing techniques, such as normalization and augmentation, further optimize the quality of the input data, ensuring that the models are trained effectively. This automated approach not only aims to reduce interobserver variability but also enhances the overall efficiency of the diagnostic process, ultimately leading to better patient management and treatment outcomes. As research in this field progresses, the synergy between radiology and artificial intelligence continues to pave the way for improved clinical practices in evaluating renal lesions.

The Bosniak classification is an important tool in determining the malignant potential of lesions, but clinicians should always adopt a multidisciplinary approach and make individualized decisions on a patient basis[11]. In this process, accurate diagnostic methods and meticulous evaluation of the findings are important for patient health and treatment outcomes.

Machine learning (ML) methods that analyze and convert data into quantitative data can give clinicians valuable information and achieve an optimized and delivered model to characterize specific tumors and CRMs[12]. Moreover, with the improvement of AI models for clinical pre-diagnosis CAD systems, Deep Learning (DL) models have gained importance in the pre-diagnosis clinical area. For this reason, DL models can be used to characterize and diagnose CRMs, especially Bosniak classification, and more successful results can be obtained in detail[13].

This study aims to develop a computerized pre-diagnosis system based on the Bosniak classification of cystic renal masses (CRM). The study aims to analyze data obtained from contrast-enhanced CT images using machine learning (ML) and deep learning (DL) models. By accurately and rapidly distinguishing the five diagnostic stages of the Bosniak classification, this system aims to provide AI-assisted support in the clinical diagnosis process, reduce interpretation variability among radiologists and clinicians, and contribute to achieving more objective results in the decision-making process.

Materials and Methods

Data Acquisition (Dataset) and Radiological Assessment

This retrospective study obtained ethical approval, and the local institutional review board waived the requirement for informed consent (approval number: 80576354–050–99/458). Our database consisted of 20 raw CT images per case stage (I, II, IIF, III, IV), and these CT examinations were performed with the renal mass analyses protocol.

An uro-oncologist and a radiologist re-evaluated the contrast-enhanced abdominal CT images of patients diagnosed with cystic renal masses (CRM) at the University Hospital. They classified them according to the Bosniak staging. Twenty CT images were selected for each Bosniak stage, for a total of one hundred images, which were taken for analysis.

Spectrogram images were mainly created and used for DL models in the data augmentation phase. Keras image processing library, such as *Imagedatagenerator*, was mainly used to increase the number and variability of images in the collected database. The augmentation operations were a randomly developed factor value, brightness modification, sharpness modification, image rotation, adding Gaussian, adding salt & pepper noise, adding speckle noise, contrast modification, image translation, zooming in an image with the segments, and flipping images. At the end of these processes, in addition to the 20 original images for each Bosniak type, 580 new images were generated through augmentation, resulting in 600 images per stage being prepared for the examination phase.

Proposed System

Our customized detection CAD system for Bosniak classification from CTs consisted of important modules detailed in figure (Figure 1).

Image Acquisition

The initial step involved uploading the test image data into the system. CT image sets in DICOM (. dcm) format were uploaded to the system at this stage. The uploaded 2D images were also rescaled to a specific resolution of 240×240 µm. This study was conducted using interface-supported tools and developed within the MATLAB 2020 and 2024 environments. The figure shows five types of images classified according to the Bosniak classification as examples (Figure 2).

Image Processing

In the pre-processing part of this study, user-defined uploaded Bosniak CT images were first converted to jpeg format. Then, the pre-processing step was performed for the next step. Images were resized to 255×255 um. In the next step, images are analyzed and converted to gray-level images. Then, these images were filtered with a 3×3 median filter to remove noise and possible artifacts from the images[14]. Due to possible insufficient contrast of the images, the contrast was adjusted. For this case,

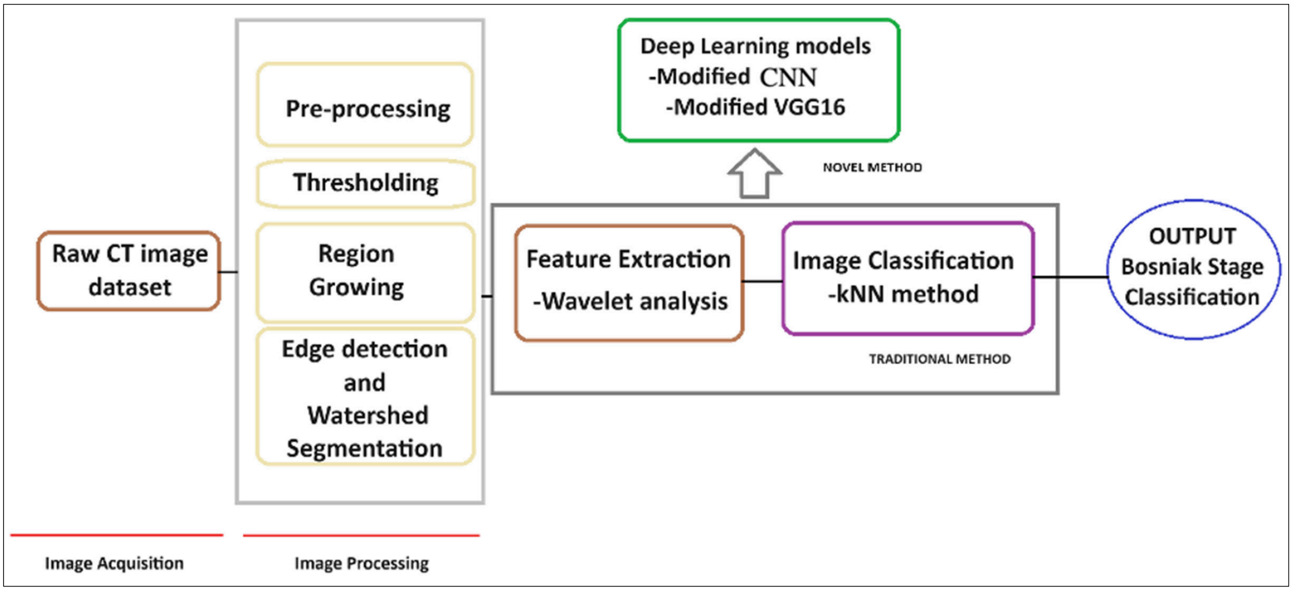

Figure 1. *Flowchart of the proposed system.*

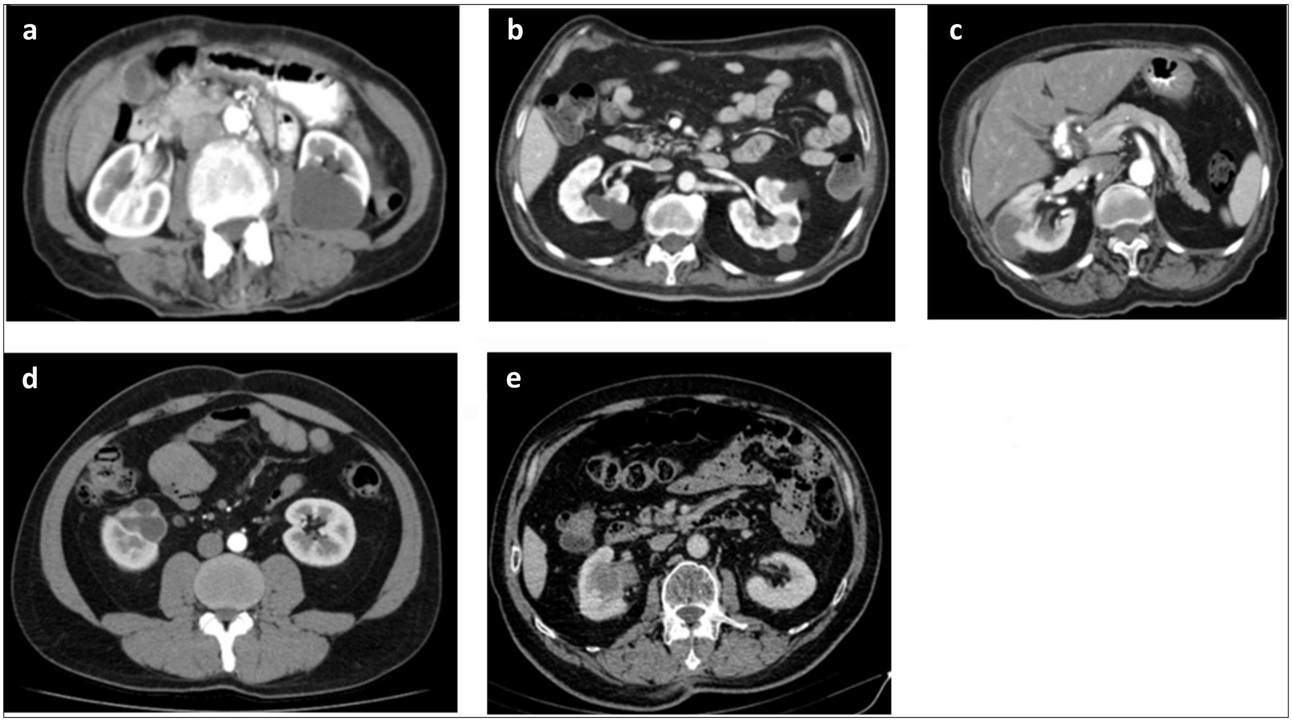

Figure 2. *Representative computed tomography images from the dataset used for evaluation, showing an example for each subtype of the Bosniak classification: Bosniak Type I (a), Type II (b), Type IIF (c), Type III (d), and Type IV (e).*

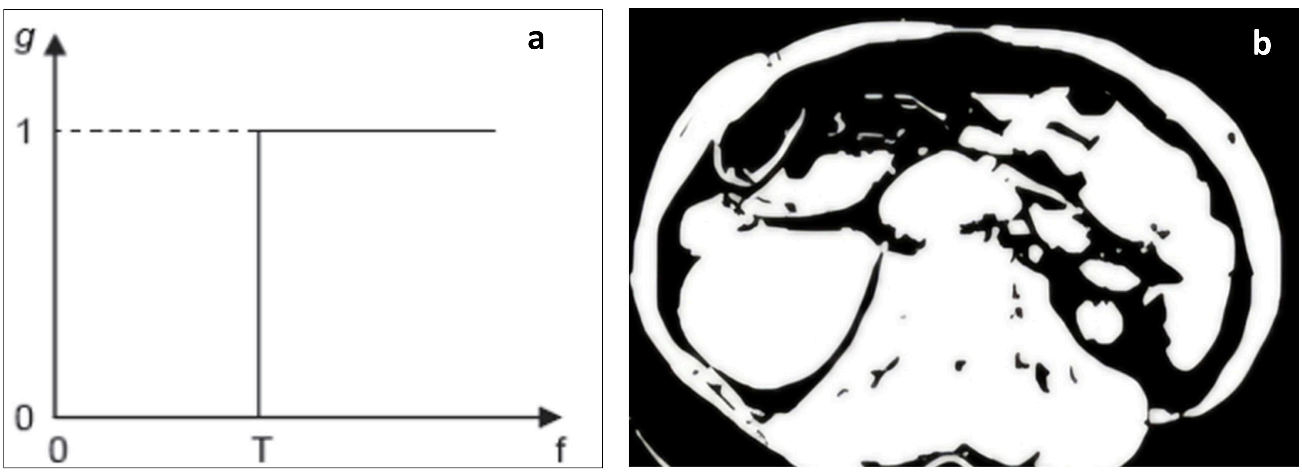

Figure 3. *Thresholding Step: (a) Single value threshold and graphical representation of the threshold for a specified value; (b) Results obtained from the thresholding process in MATLAB.*

an improved cubic curve contrast enhancement method was used to increase the texture, and images became clearer[15].

The other step was Thresholding. This section showed that abnormal areas in radiological images became white after a certain threshold, other parts of the image were eliminated, and the black color tone was highlighted[16]. Then, the highlighted images most likely indicated the region and regions included in the mass. The process continues to the next stage, which is the interpretation of the regions. For this stage, a hybrid method combining Gray level and Otsu thresholding methods was used and applied to the images. Contrast was the image's darkest parameter and could be defined as the difference between the brightest area[17]. Traditionally, thresholding was a simple way to perform the section to set a range of brightness values in the original image. Then, the pixels within the range as foreground were selected, and all other areas were to

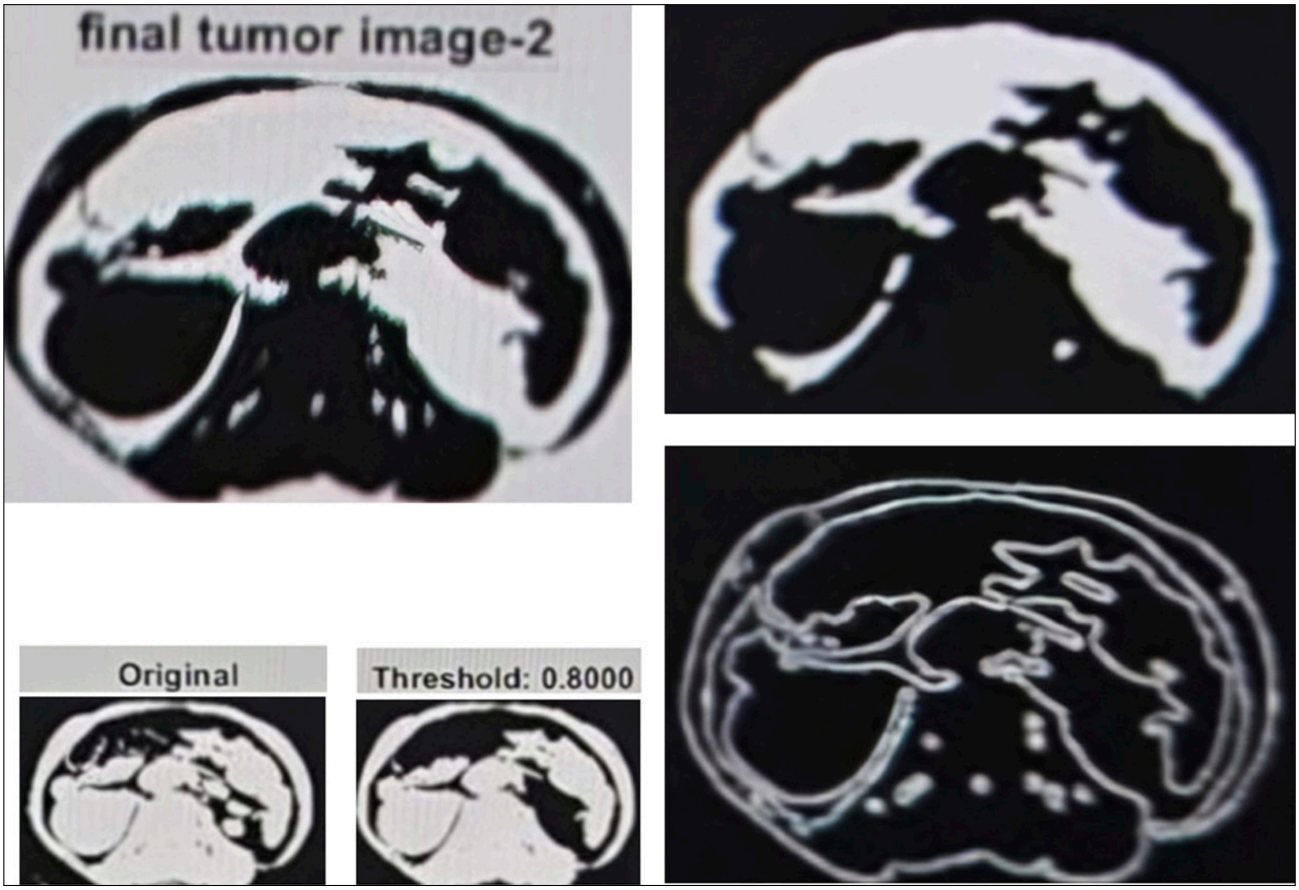

Figure 4. *Region-growing results in MATLAB*

reject pixels in the background. The figure shows the thresholding process, including the single value threshold and a graphical representation (Figure 3a), with the process results presented in MATLAB (Figure 3b).

The other step was Region Growing. In this step, Sobel edge detection and marker-controlled Watershed segmentation methods were chosen and used, and a hybrid Region growing process was achieved. For this step, images obtained were given in MATLAB in figure (Figure 4). The pseudocode of the hybrid region growing method was given in detail in figure (Figure 5).

Feature Extraction and Traditional Classification with ML Methods

In determining and interpreting abnormal areas, feature extraction was performed first on the mass areas[18]. This step included medical and image processing areas (Contrast, Correlation, Homogeneity, Variance, Energy, Entropy, External Curvature, Mean, Standard Deviation, etc.) that were obtained as numerical data for regions, and the analyzing process was achieved. The 14 features mentioned in the figure are given in detail (Figure 6).

In the classification via Machine Learning (ML) methods stage, k Nearest Neighbor (kNN) was a classification method used in data mining. This method performed the classification process according to the class of the nearest neighbor as much as the k value given. In the kNN method, the distance of the test data to the training data was obtained by the Euclidean method[19]. In the classification phase with kNN mentioned above, 20 and 730 CT images per Bosniak class were used and 14 features were obtained totally and these matrixes were saved to an Excel file for fedding into the ML model for classification and interpretation.

Transfer Learning-DL Approaches

In the experimental part, a transfer learning approach was performed to analyze and evaluate the performance metrics of the common ML and modified DL deep models on the Bosniak CT dataset. In this phase, feature extraction was not needed for the DL part, and the spatial characteristics of EEG data were extracted using the CNN network[20]. The developed CNN model algorithm was formulated and given below.

```
%region growing
    im=im2double(BW);
    T=0.8;
    [r,c]=size(im);
    A=zeros(r,c); % segmented mask
    F=[]; % frontier list
    subplot(1,2,1);
    imshow(im);
    title('Original');
    imwrite(im,'processedimage.jpg')
    s=uint16(ginput(1));     % get the click coordinates
    s=[s(2),s(1)];       % [row,col]
    A(s(1),s(2))=1;
    F=[F;s];
    while(~isempty(F)) % if frontier is empty
        n=neighbours(F(1,1),F(1,2),r,c);    % 4 neighbourhood
        for i=1:size(n,1)
            if(abs(im(F(1,1),F(1,2))-im(n(i,1),n(i,2)))<T && A(n(i,1),n(i,2))~=1)
                A(n(i,1),n(i,2))=1;
                F=[F;n(i,1),n(i,2)];
            end
        end
        F(1,:)=[];
    end
    subplot(1,2,2);
    imshow(A);
    title(sprintf('Threshold: %0.4f',T));
```

```
sobel edge detection
W1 = edge(A,'Canny');
igure,imshow(BW1)
mshowpair(BW1,BW,'montage')
%marker controlled watershed seg.
fm=A;
e = strel('disk', 2);
top = imtophat(afm, se);
bot = imbothat(afm, se);
igure, imshow(Itop, []), title('top-hat image');

igure, imshow(Ibot, []), title('bottom-hat image');

=imadd(Itop, afm);
hos X
hos Ibot
bot=im2double(Ibot);

enhance = imsubtract(X, Ibot);
igure, imshow(Ienhance), title('final tumor image')
image enhancement
ec = imcomplement(Ienhance);
igure, imshow(Iec), title('final tumor complement image-1');

emin = imextendedmin(Iec,1);
impose = imimposemin(Iec, Iemin);
igure, imshow(Iemin), title('extended minima image');
igure, imshow(Iimpose), title('final processed image-2');
```

Figure 5. *Pseudocodes of hybrid region growing method.*

Algorithm: Convolutional Neural Network (CNN)

1. Input: Number of samples, channels

2. $a_b^l = \sum_{c \in r} a_c^{l-1} \otimes K_{bc}^l + d_b^l$

3. The features belonging to the signals were down sampled in an average small neighborhood for obtaining new features after the convolution process. Indeed, the pooling process was achieved via the formula given below.

$$F = f(a_b^l = \sum_{c \in r} a_c^{l-1} \otimes K_{bc}^l + d_b^l) =$$

$$f(x_c^l \mathrm{down}(a_c^{l-1}) + d_b^l)$$

4. The output was the first fully connected layer, and this could be obtained by weighting the input via the given formula

$$u^I = w^I a^{I-1} + d^I$$

For the equations given above,

```
seg_img=Iec;
% Extract features using DWT
x = double(seg_img);
m = size(seg_img,1);
n = size(seg_img,2);
signal1 = seg_img(:,:);

[cA1,cH1,cV1,cD1] = dwt2(signal1,'db4');
[cA2,cH2,cV2,cD2] = dwt2(cA1,'db4');
[cA3,cH3,cV3,cD3] = dwt2(cA2,'db4');

DWT_feat = [cA3,cH3,cV3,cD3];
G = pca(DWT_feat);

[g] = graycomatrix(G);
%stats = graycoprops(g,{'contrast','homogeneity','correlation','Energy'});
stats = graycoprops(g,'Contrast Correlation Energy Homogeneity');

Contrast = stats.Contrast;
%sprintf('Contrast is: %g%%',Contrast)

Correlation = stats.Correlation;

Energy = stats.Energy;

Homogeneity = stats.Homogeneity;

Mean = mean2(G);

Standard_Deviation = std2(G);
```

```
Entropy = entropy(G);

RMS = mean2(rms(G));

Variance = mean2(var(double(G)));

a = sum(double(G(:)));
Smoothness = 1-(1/(1+a));

Kurtosis = kurtosis(double(G(:)));

Skewness = skewness(double(G(:)));

% Inverse Difference Movement
m = size(G,1);
n = size(G,2);
in_diff = 0;
for i = 1:m
    for j = 1:n
        temp = G(i,j)./(1+(i-j).^2);
        in_diff = in_diff+temp;
    end
end
IDM = double(in_diff);
%white area calculation
nWhite_pixels=sum(Iec(:));
[rows columns depth]=size(Iec);
percentage_of_white_area=(nWhite_pixels/(rows*columns))*100;
disp(percentage_of_white_area);
```

Figure 6. *Pseudocodes of Feature Extraction process and the obtained features.*

a_b^l: the mth channel activation value,

a_c^{l-1}: the mth channel output,

f(·): the activation function,

p: the selected feature sets of input,

K_{bc}^l: a convolution function,

d_b^l: the bias value,

x_c^l: the offset coefficient,

x_c^l, d_b^l: the bias coefficients,

a_b: the activation value of the fully connected layer,

w^l : the weight of the fully connected layer.

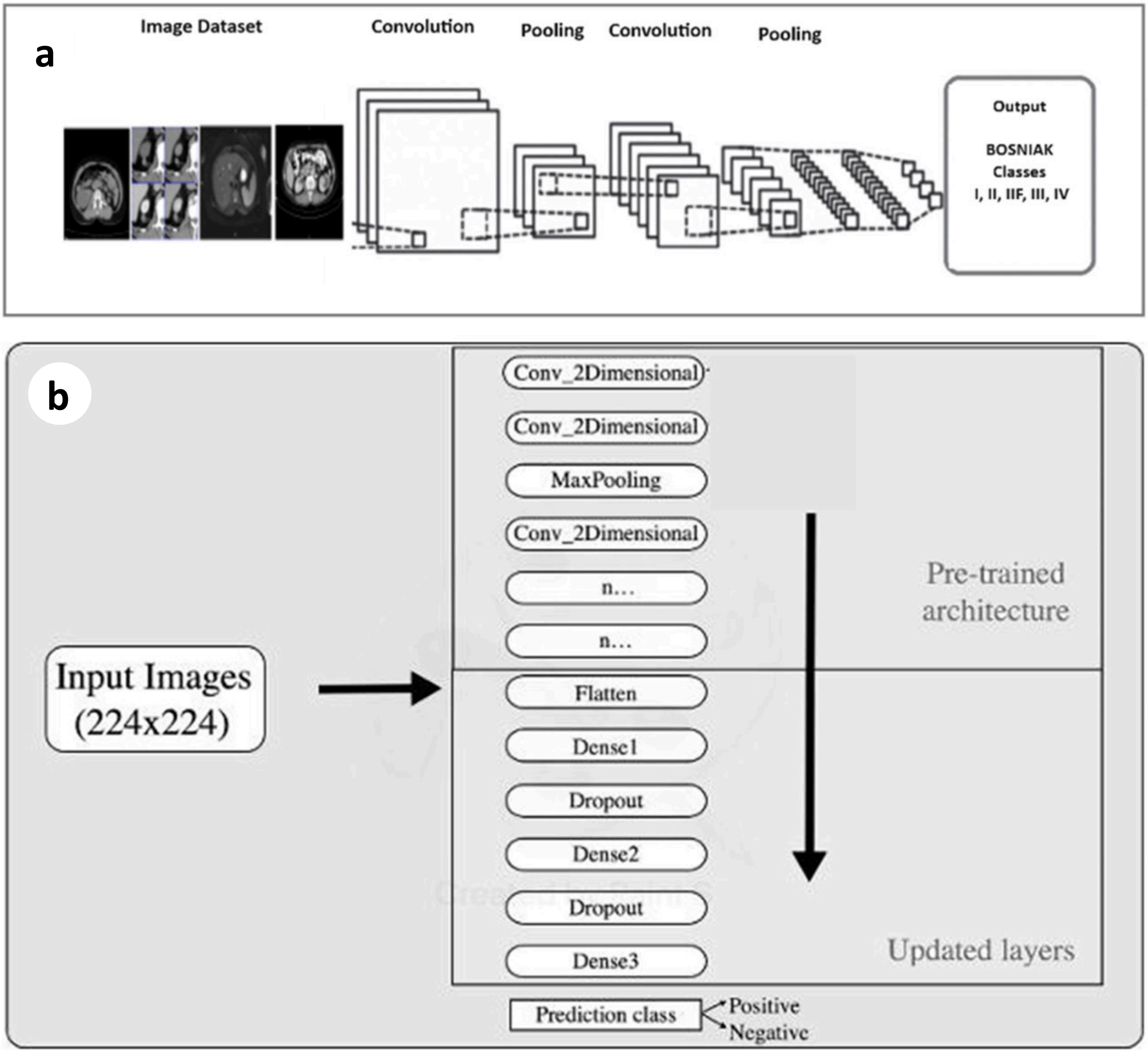

Figure 7. *The architectures of the models used in the study are shown: CNN model architecture (a) and VGG16 modified model architecture (b).*

For this model, the parts of the fundamental model were the pre-trained phase, up-to-date layer and estimation class. Using MATLAB environment, the CNN model has eight constant layers; other parts could be improvable. For the fully connected phase, Artificial Neural Networks (ANNs) were performed in detail. According to the total model, 17 Convolutional Neural Network (CNN) layers were used[21]. After filtering, a Maximum Pooling layer and dense and drop-out layers gathered this layer. In the figure, the CNN model was given in detail (Figure 7).

In addition, 10-fold cross-validation was chosen to eliminate the influence of the selected training and test data for the model evaluation. The equations are given below,

m: the number of samples,

$\hat{}y_n$: the predicted value, y_n: the real value.

$$CV_e = 0.1 \text{ x } \sum_{k=1}^{10} e_k$$

$$e_k = \frac{1}{m} x \ \sum_{l=1}^{m}((\hat{}y_n - y_n)^2$$

Results

The experimental part of the study was achieved via MATLAB 2020 and 2024 versions with an 11 th Generation Intel brand i7–11900 processor, 2.500Ghz, 64GB DDR4 memory, and 1024GB SD storage capacity in detail. Indeed, these images were then anonymized

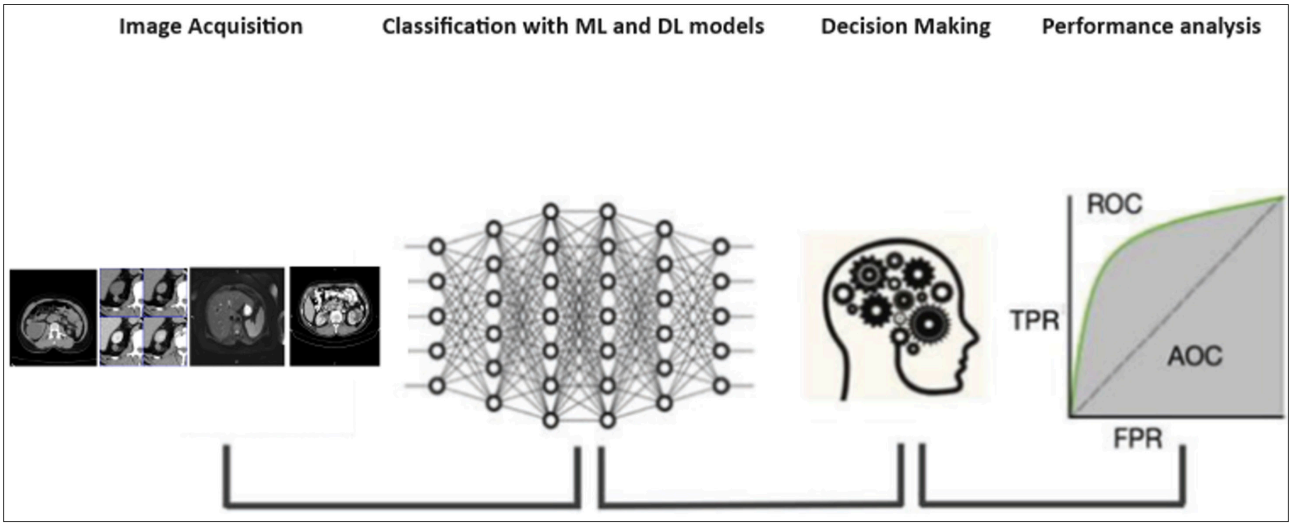

Figure 8. Performance evaluation of the proposed system.

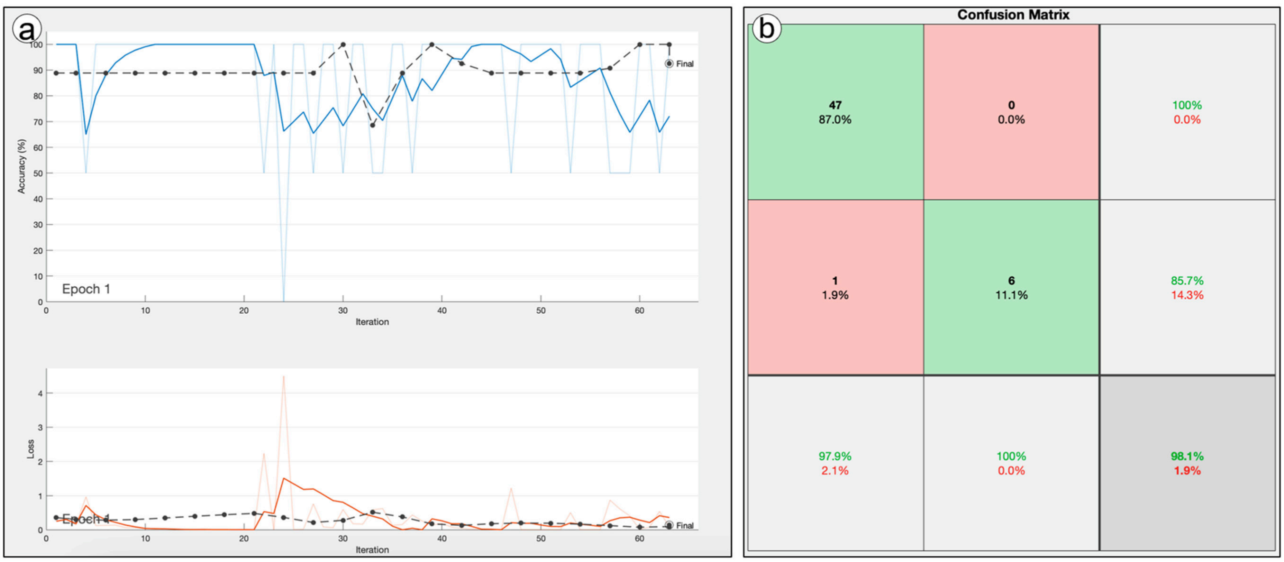

Figure 9. Obtained accuracy and loss results for the CNN model (a); Confusion matrix for the CNN model (b).

and preprocessed through signal labeling using the MATLAB tool. The performance calculation procedure of the whole system is given in Figure (Figure 8).

CT images were processed as the first step in the experimental part, and Feature Extraction was performed. With the wavelet method, features were obtained, and these feature matrix (gray matrix) was classified with the common Machine Learning kNN algorithm. According to the results, the classification accuracy was obtained with the 85% for Bosniak classification for kNN classifier.

Then, the next part was classification with DL models and modified CNN and VGG16 models were used in the classification stage. According to the figure, the ROC AUC curve and confusion matrix for the CNN model were given in detail (Figure 9). The CNN model has achieved more complex classification results with 98% with better capabilities. In Figure, the accuracy results for the confusion matrices of VGG16 for 10-fold cross-validation were given in detail (Figure 10).

According to the confusion matrices above, the last model (VGG16) approach reduced the misclassifications. According to the models, the best accuracy was obtained from the VGG16 deep model compared to the CNN model.

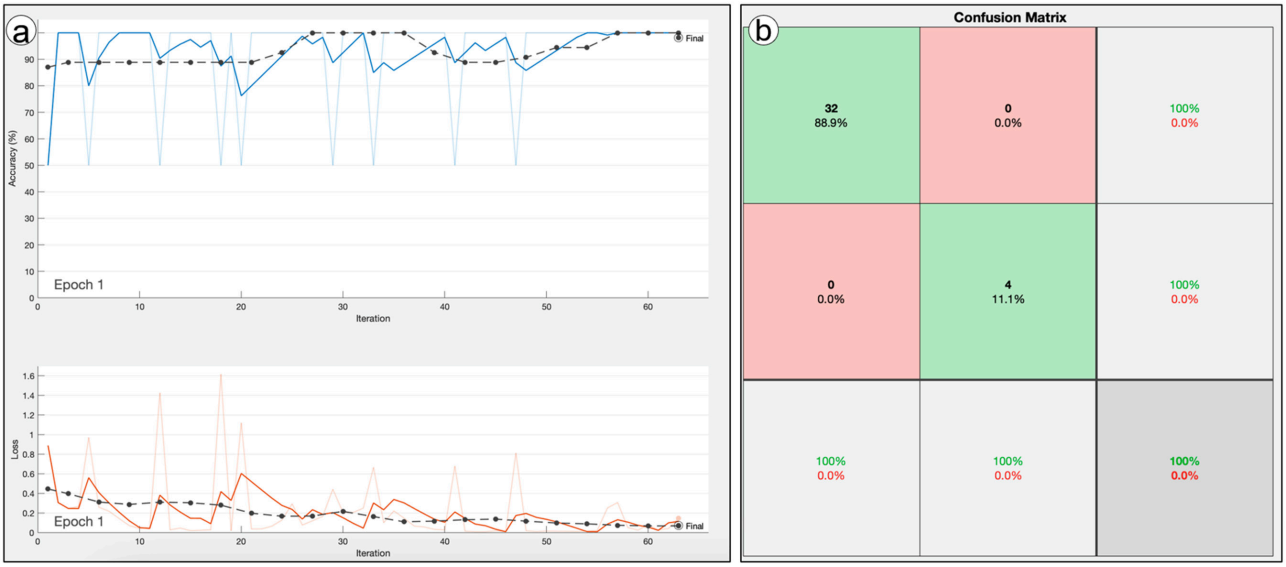

Figure 10. *Obtained accuracy and loss results for the VGG16 model (a); Confusion matrix for the VGG16 model (b).*

Discussion

In this study, we hypothesized that an improved version of CT-based machine learning and modified deep learning algorithms could be used to classify cystic renal masses more successfully in the Bosniak Classification System. Our results showed significant differences in some texture parameters and features, including mean, deviation, entropy, kurtosis and skewness. Entropy represents the total irregularity in the gray-level intensities of a lesion or mass.

According to the ML classification, the accuracy result was obtained as 85% for the kNN algorithm. Indeed, according to the classification with modified DL models, the accuracy result was obtained for the CNN model, and the accuracy result was obtained as 98% for the VGG16 model. When we analyzed all the results, the highest and best results were obtained from the VGG16 classifier and then the kNN classifiers. Indeed, every training and classification results were different from each other for detecting the mental disease case.

Even while our suggested model performed well in classification on datasets with significant imbalances or few samples, it was still far from perfect and contained flaws. For instance, the training and labeling of the photos for the sample preparation in our suggested model required significant processing power, and the training speed was comparatively slow. As a result, we will provide more image labeling and samples in our future work to improve the detection quality, as it has been demonstrated that some diseases are still not correctly diagnosed because of inadequate data sources. All models used in the study could be successfully used for different cases or CT types to help clinicians via CAD pre-diagnosis systems.

Limitations

One of the main limitations of this study is the limited number of patients available for each Bosniak stage. Particularly for the rarer subtypes, such as Bosniak type III and IV, we had a limited number of patients in our dataset. Thus, we aimed to utilize the maximum number of patients from the available data pool. To partially address this limitation, synthetic data were generated through image augmentation, a technique frequently employed in machine learning systems. However, when compared to raw data from real patients, the clinical validity of these augmented images remains a topic of debate. Despite this, the study provides a valuable contribution by offering a different approach compared to similar studies in the literature. Utilizing larger datasets in future research will enhance the accuracy and reliability of the model and strengthen the generalizability of the findings.

Additionally, the artificial intelligence models used in this study are based solely on imaging data. Factors such as the patient's symptoms, laboratory results, and overall condition should also be considered in clinical decision-making. Therefore, adopting a more comprehensive and multidisciplinary approach will not only improve the model's accuracy but also facilitate its integration into clinical practice.

Conclusion

In this study, the computerized AI-based version of Bosniak classification was mainly achieved. Indeed, these were performed by the common ML method and the trend DL model. According to the ML classification, the accuracy result was obtained as 85% for the kNN algorithm. Indeed, according to the classification with modified DL models, the accuracy result was obtained as for CNN model and the accuracy result was obtained as 98% for VGG16 model. Diagnosing renal cysts at a curable stage has become important and gained importance in the medical area. Also, it was important to reduce the overuse, overdiagnosis procedures, etc. Indeed, the Bosniak classification was generally used to distinguish benign from malignant masses. The CT-based Bosniak classification system can accurately diversify the five diagnosis types, and this system can be achieved with other CRM types. It has good performance metrics, which may facilitate treatment decision-making and is less affected by interobserver disagreements.

References

1. Alrumayyan M, Raveendran L, Lawson KA, Finelli A. Cystic Renal Masses: Old and New Paradigms. Urol Clin North Am. 2023;50(2):227–238.
2. McGrath TA, Bai X, Kamaya A, Park KJ, Park MY, Tse JR, et al. Proportion of malignancy in Bosniak classification of cystic renal masses version 2019(v2019) classes: systematic review and meta-analysis. Eur Radiol. 2023;33(2):1307–1317.
3. Silverman SG, Pedrosa I, Ellis JH, Hindman NM, Schieda N, Smith AD, et al. Bosniak Classification of Cystic Renal Masses, Version 2019: An Update Proposal and Needs Assessment. Radiology. 2019;292(2):475–488.
4. Narayanasamy S, Krishna S, Prasad Shanbhogue AK, Flood TA, Sadoughi N, Sathiadoss P, et al. Contemporary update on imaging of cystic renal masses with histopathological correlation and emphasis on patient management. Clin Radiol. 2019;74(2):83–94.
5. Miskin N, Qin L, Silverman SG, Shinagare AB. Differentiating Benign From Malignant Cystic Renal Masses: A Feasibility Study of Computed Tomography Texture-Based Machine Learning Algorithms. J Comput Assist Tomogr. 2023;47(3):376–381.
6. Zeng SE, Du MY, Yu Y, Huang SY, Zhang D, Cui XW, et al. Ultrasound, CT, and MR Imaging for Evaluation of Cystic Renal Masses. J Ultrasound Med. 2022;41(4):807–819.
7. Warren KS, McFarlane J. The Bosniak classification of renal cystic masses. BJU Int. 2005;95(7):939–942.
8. Curry NS, Cochran ST, Bissada NK. Cystic renal masses: accurate Bosniak classification requires adequate renal CT. AJR Am J Roentgenol. 2000;175(2):339–342.
9. Hindman NM, Hecht EM, Bosniak MA. Follow-up for Bosniak category 2F cystic renal lesions. Radiology. 2014;272(3):757–766.
10. Aronson S, Frazier HA, Baluch JD, Hartman DS, Christenson PJ. Cystic renal masses: usefulness of the Bosniak classification. Urol Radiol. 1991;13(2):83–90.
11. Smith AD, Remer EM, Cox KL, Lieber ML, Allen BC, Shah SN, et al. Bosniak category IIF and III cystic renal lesions: outcomes and associations. Radiology. 2012;262(1):152–160.
12. Zakaria MA, El-Toukhy N, Abou El-Ghar M, El Adalany MA. Role of multiparametric MRI in characterization of complicated cystic renal masses. Egyptian Journal of Radiology and Nuclear Medicine. 2023;54(1):1–13.
13. Lin Z, Cui Y, Liu J, Sun Z, Ma S, Zhang X, et al. Automated segmentation of kidney and renal mass and automated detection of renal mass in CT urography using 3D U-Net-based deep convolutional neural network. Eur Radiol. 2021;31(7):5021–5031.
14. Huang L, Ye Y, Chen J, Feng W, Peng S, Du X, et al. Cystic renal mass screening: machine-learning-based radiomics on unenhanced computed tomography. Diagn Interv Radiol. 2024;30(4):236–247.
15. Zhang J, Tehrani YM, Wang L, Ishill NM, Schwartz LH, Hricak H. Renal masses: characterization with diffusion-weighted MR imaging--a preliminary experience. Radiology. 2008;247(2):458–464.
16. Krishna S, Murray CA, McInnes MD, Chatelain R, Siddaiah M, Al-Dandan O, et al. CT imaging of solid renal masses: pitfalls and solutions. Clin Radiol. 2017;72(9):708–721.
17. Mangayarkarasi T, Jamal DN. PNN-based analysis system to classify renal pathologies in Kidney Ultrasound Images. International Conference on Computing and Convergence Technology. 2017;123–126.
18. Brandi N, Mosconi C, Giampalma E, Renzulli M. Bosniak Classification of Cystic Renal Masses: Looking Back, Looking Forward. Acad Radiol. 2024;31(8):3237–3247.
19. Kang H, Xie W, Wang H, Guo H, Jiang J, Liu Z, et al. Multiparametric MRI-Based Machine Learning Models for the Characterization of Cystic Renal Masses Compared to the Bosniak Classification, Version 2019: A Multicenter Study. Acad Radiol. 2024;31(8):3223–3234.
20. Bhandari M, Yogarajah P, Kavitha MS, Condell J. Exploring the Capabilities of a Lightweight CNN Model in Accurately Identifying Renal Abnormalities: Cysts, Stones, and Tumors, Using LIME and SHAP. Applied Sciences 2023, Vol. 13, Page 3125. 2023;13(5):3125.
21. Zabihollahy F, Schieda N, Krishna S, Ukwatta E. Automated classification of solid renal masses on contrast-enhanced computed tomography images using convolutional neural network with decision fusion. Eur Radiol. 2020;30(9):5183–5190.