Indonesian Journal of Electrical Engineering and Computer Science
Vol. 31, No. 3, September 2023, pp. 1829~1838
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v31.i3.pp1829-1838

Kidney stones detection based on deep learning and discrete wavelet transform

Fouad Shaker Tahir, Asma Abdulelah Abdulrahman
Department of Applied Sciences Mathematics and Computer Applications, University of Technology, Baghdad, Iraq

Article Info

Article history:

Received Jan 30, 2023
Revised May 20, 2023
Accepted May 27, 2023

Keywords:

Convolution neural network
Deep learning
DFCWT
Medical images
Wavelet transformation

ABSTRACT

The problem of the research is to find medical images of purity, high quality and free of impurities, which contributes to enabling doctors to obtain the results of analyzing the health status of each patient according to his disease data. Therefore, it was necessary to use discrete first chebysheve wavelets transform (DFCWT) technique in order to remove the associated impurities that appear in the medical images, and then analyze the results for all of the above, the algorithm DFCWT has been combined with and linking it to a neural network based on convolutional neural network (CNN) and this contributes to obtaining the results of analyzing image data with high accuracy and speed. The new algorithm proposed in this paper is based on deep learning finding the identification of kidney stones using DFCWT and the same process can be repeated on skin cancer, bones and fractures, processing by discrete first chebyshev wavelet transformation convolution neural network (DFCWTCNN).

Corresponding Author:

Asma Abdulelah Abdulrahman
Department of Applied Sciences Mathematics and Computer Applications, University of Technology
Baghdad, Iraq
Email: asma.a.abdulrahman@uotechnology.edu.iq

1. INTRODUCTION

The role of artificial intelligence in the medical field as well as in many other fields is shown through deep learning in general and the convolutional neural network in particular, there has been interest in artificial intelligence and deep learning recently due to the large and massive amounts of data that need to be examined and knowledge of the sample being examined [1], [2]. Diab *et al.* [3] deep learning and convolutional neural network training were used to detect brain tumors, especially ResNet50 was used, with an accuracy of 99.8% with an error of 0.005. As for skin cancer, it was detected in [4] by using convolutional neural networks for early disease recognition using the classifier (SVM). GoogleNet, ResNet-50, AlexNet, and VGG19 were examined and compared. and reach an accuracy of 99.8%. On the other hand, deep learning is involved in gender recognition where convolutional neural networks were used through ancestral images in natural conditions with deep learning, and an accuracy of 89% was reached in [5]. The need for deep learning accuracy was required around the world during the period in which the corona virus spread, so that the diagnosis could be made quickly without delay, and the diagnosis of pneumonia with an accuracy of 97.5%, which is considered a good percentage and when the term pandemic was announced in 2020, the test was called (RT-PCR) to diagnose the virus [6], [7]. Asma and Fouad they worked extensively in the field of deep learning by using networks CNN GoogleNet, AlexNet to recognize the face and know facial feelings with the help of discrete wavelets DWTCNN and improve images in addition to watermarks and image processing with DCHWT [8]–[18]. A lot of work in 2020 and after that, the deep learning process took place in two stages, which is the pre-processing to prepare the image for deep learning in terms of removing noise and compressing the image to reduce the space occupied by the image data, depending on the discrete wavelets and the second stage is connecting the wavelets to the convolutional neural network, which it leads to obtaining accurate results because through it or in the preliminary stage, image quality standards are measured [19]–[27]. Here, the goal of this work appears instead of using basic discrete wavelets prepared in the MATLAB program such as haar symlet 2, coiflet 2, and daubecheis 2, but the required results were not reached [28]–[40].

This work will be organized as follows in section 2. The workflow diagram and new wavelet construction DFCWT are constructed. In section 3 discusses the training of the neural network based on the convolutional neural network after compression and analysis. In section 4 provides a new and fast algorithm and computation of the obtained results regarding the image quality criteria, signal-to-noise ratio (PSNR), mean square error (MSE), compression ratio (CR) and bit-per-pixel (BPP) that led to the calculation of accuracy and the accuracy of the comparison between the results obtained before and after using the new technology, which proved the efficiency of the proposed algorithm in detecting an object using the discrete first chebyshev wavelet transformation convolution neural network (DFCWTCNN), section 5 discusses the results that have been reached and high accuracy with clarity of kidney stone detection and high accuracy with calculating the error rate in this work using the proposed technique, Figure 1 shows how to use DFCWTCNN to improve the sample used. In this work where the comparison between the use case of the convolutional neural network without the new filter and the use case of the convolutional neural network with the new filter proposed in this paper.

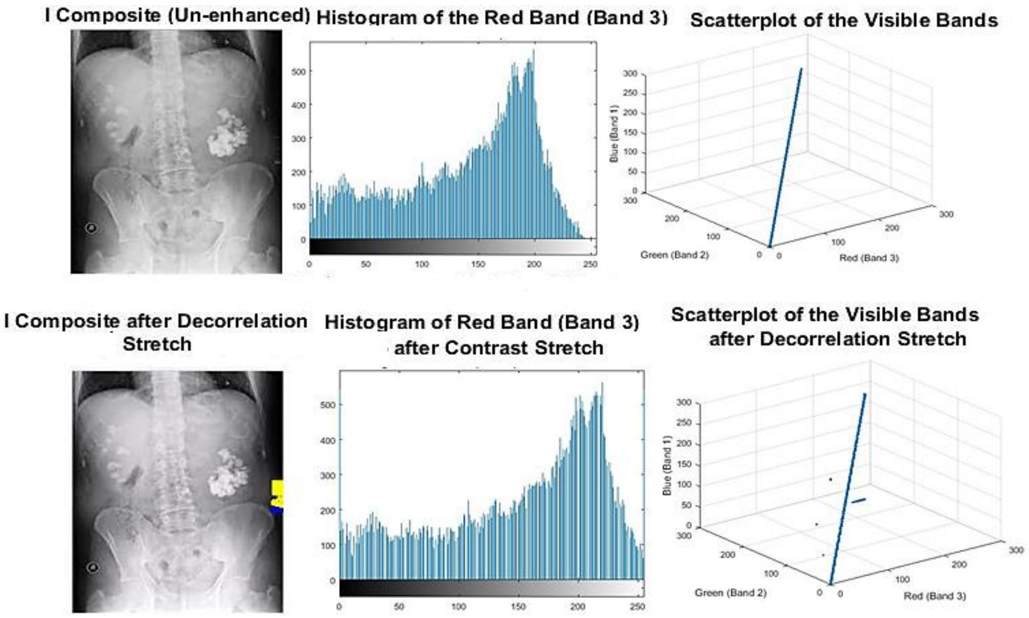


Figure 1. Histogram image optimization and post-optimization

2. METHOD

In the past many years, many methods have been used to identify infected objects using the basic discrete wavelet transform equipped in the MATLAB program to improve the medical image kidney stones to improve the image by removing noise and compressing the image and to improve the image quality values by measuring the MSE, PSNR, BPP, and CR. After the development of improved object detection, the training of a convolutional neural network for deep learning of various types was used by training the network Alex Net and Google Net. The proposed theory begins by highlighting the role of the proposed wavelets in analysing the medical image to be improved after removing the noise from the image. The work is traced back to the Figure 2 to divide the figure into two parts, the first represents the pre-processing process, and the second part is detection after training the convolutional neural network to detect kidney stones. Equations of discrete wavelet transformation (DWT) derived from first chebyshev polynomials because of their importance in dealing with image processing in the field of multi resolution analyses due to the orthogonally and convergent characteristic of these wavelets.

2.1. Discret wavelet transformation

The construction of wavelets through expansion and contraction of the effect of the modulus (e, f), which is called the wavelet mother in (1);

$$\mu_{e,f}(x) = |e|^{-\frac{1}{2}}\mu\left(\frac{t-f}{e}\right) \quad e,f \in R,\ R \neq 0 \tag{1}$$

the bases vector;

$$[\mu_0(x), \mu_1(x), \dots, \mu_{M-1}(x)]^T \tag{2}$$

satisfied equation;

$$\int \mu(x)\,dx = 0 \qquad in\ R \tag{3}$$

discrete first chebyshev wavelet transformation (DFCWT) constructed from (1) reached to DFCWT of the following equations the wavelets are divided into scaling function $\partial(t)$in $V_n$space and first chebyshev wavelet $\delta(x)$ in wavelet space W_n $\delta_{u,v}(t) = \delta_{t,u,v,k}$ $\quad k = 1,2 \quad u = 1,2, \dots, 2^{k-1}$, v is the order of first chebyshev polynomials, the transform DFCWT $e = 2^{-(k-1)}$ and $f = 2^{-(k+1)}(2u-1)$for transform, $x = 2^{-(k-1)}(2^k t)$ in (1).

$$\delta_{u,v}(t) = 2^{-(k)}\tilde{\delta}_{u,v}\left(\frac{2^{-(k)}(2^{k+1}t) - 2^{-(k)}(2u-1)}{2^{-(k)}}\right) \tag{4}$$

$$\delta_{u,v}(t) = \begin{cases} \frac{\sigma_v 2^{\frac{k}{2}}}{\sqrt{\pi}}\tilde{\vartheta}_{u,v}(2^{k+1}t - 2u + 1) & \frac{u-1}{2^k} \leq t \leq \frac{u}{2^k} \\ 0 & otherwise \end{cases} \tag{5}$$

$$\sigma_v = \begin{cases} \sqrt{2} & v = 0 \\ 2 & v = 1, 2, \dots \end{cases} \text{for v=0, 1, 2, …}$$

$$\vartheta_0(t) = 1, \vartheta_1(t) = t$$

$$\vartheta_v(x) = 2x\vartheta_{v-1}(x) - \vartheta_{v-2}(x) \qquad v = 2, 3, \dots,$$

If take $u = 1, 2$ and $v = 1,2, \dots, M-1$, the following based functions for u=1, 2 and v=0, 1, 2 for M=3;

$$\left.\begin{aligned} \delta_{1,0}(t) &= \frac{2}{\sqrt{\pi}} \\ \delta_{1,1}(t) &= \frac{2\sqrt{2}}{\sqrt{\pi}}(4t-1) \\ \delta_{1,2}(t) &= \frac{2\sqrt{2}}{\sqrt{\pi}}(32t^2 - 16t + 1) \end{aligned}\right\} t \in \left[0, \frac{1}{2}\right), \quad \left.\begin{aligned} \delta_{2,0}(x) &= \frac{2}{\sqrt{\pi}} \\ \delta_{2,1}(x) &= \frac{2\sqrt{2}}{\sqrt{\pi}}(4t-3) \\ \delta_{2,2}(x) &= \frac{2\sqrt{2}}{\sqrt{\pi}}(32t^2 - 48t + 17) \end{aligned}\right\} t \in \left[\frac{1}{2}, 1\right) \tag{6}$$

then $F(t) \in L_2(0, 1]$ is the approximate function;

$$F(t) = \sum_{u=1}^{2^{k+1}}\sum_{v=0}^{M-1} C_{u,v}\,\delta_{u,v}(x) = C^T\delta(t) \tag{7}$$

the two matrices, δ and by $2^{k+1}M \times 1$;

$$C = \left[C_{10}, C_{11}, \dots, C_{1(M-1)}, C_{20}, \dots, C_{2(M-1)}, \dots, C_{2^{k+1}}, \dots, C_{2^{k+1}M-1}\right]^T \tag{8}$$

$$\delta(t) = \begin{bmatrix} \delta_{1,0}(t), \delta_{1,1}(t), \dots, \delta_{1,M-1}(t), \delta_{2,0}(t), \dots, \delta_{2^{k+1},M-1}(t), \\ \dots\delta_{2^{k+1},0}(t), \dots\delta_{2^{k+1}M-1}(t) \end{bmatrix}^T \tag{9}$$

$$\partial(x) = \begin{cases} 1 & if\ 0 \leq t \leq 1 \\ 0 & otherwise \end{cases} \tag{10}$$

approximation coefficients and details for DFCWT to be the signal in the (11).

$$\rho_{u,v} = \int S(t)\delta_{u,v}(t)dt \quad in\ R \tag{11}$$

$$\vartheta_{u,v} = \int S(t)\partial_{u,v}(t)dt \quad in\ R \tag{12}$$

DFCWT filter will be $u = 0, 1, 2$ then $v = 0,1,2, \dots, 2^u - 1$ if $u = 0$, $\partial_{0,0}(t) = \delta_{0,0}(t) = \frac{2}{\sqrt{\pi}} \subset V_0$, $u = 1$, $\delta_{1,0}(t) = \sqrt{2}\,\delta_{0,0}(2t) = \sqrt{2} \subset W_0$ $\quad \delta_{1,1}(x) = \sqrt{2}\,\delta_1(2t-1) = \sqrt{2}[1-(2t-1)] \subset W_1$ same processed for $v = 2, \dots, 2^u - 1$ then low pass filter $\begin{bmatrix} \frac{2}{\sqrt{\pi}} \\ \frac{2}{\sqrt{\pi}} \end{bmatrix}$and the high pass filter $\begin{bmatrix} \frac{-2}{\sqrt{\pi}} \\ \frac{2}{\sqrt{\pi}} \end{bmatrix}$

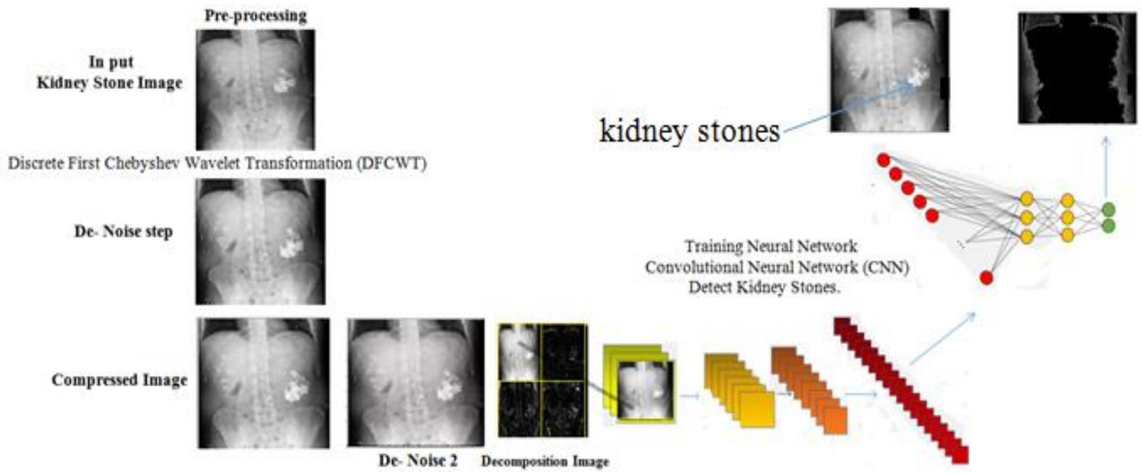


Figure 2. Divide the process to two parts, the first represents the pre-processing process and the second part is detection after training the convolutional neural network to detect kidney stones

2.2. Pre-processing with the new filter DFWT

The proposed new technique is to analyze the color image, which is a matrix when it is factored with DFCWT to perform the multi resolution analyses (MRA) operation so that the image parameters are divided into two parts, the approximate coefficients and details coefficients, where the first is concentrated in the first quadrant, while the second coefficients are distributed over the remaining three quadrants and quadrants are LL, HL, LH, and HH, when taking the inverse IDFCWT is returned to the original image without losing the original image informations this process in Figure 3. The possibility that the medical image contains noise, which leads to the body not being identified well or precisely, where the new discrete wavelets DFCWT were used to remove the noise from the medical image without affecting the quality of the image. Through the inverse of the waves IDFCWT, the process of reconstruction of the image takes place. Figure 4 shows the medical image after removing the noise from it.

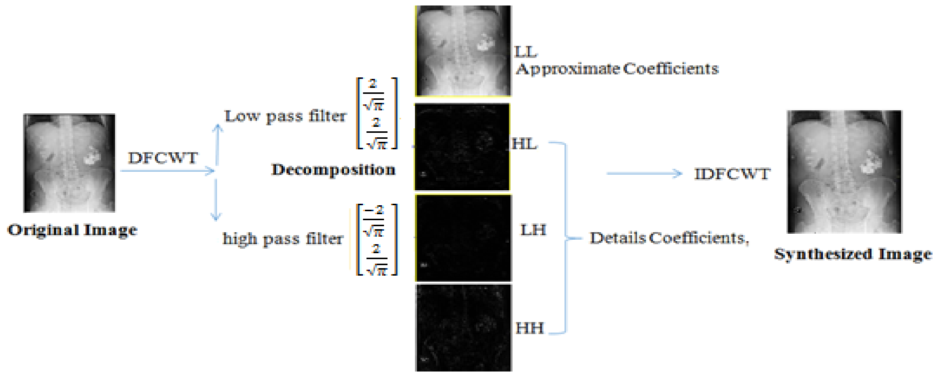
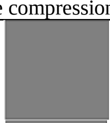
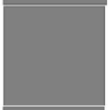
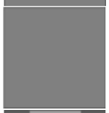
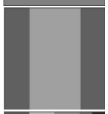
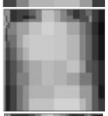
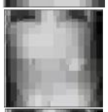
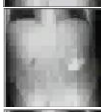
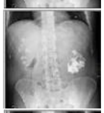


Figure 3. Analysis of color medical images using DFCWT

Figure 4. Image without noise with DFCWT

In the pre-processing for processing the medical image, after analysing the image and taking the quadrant that contains the approach coefficients, to remove the noise, and then compress the image to calculate the image quality criteria. Table 1 represents the stages of image compression.

Table 1. Represents the stages of image compression

loop	Image compression steps	MSE	PSNR	BPP	CR
1		4,741	11.37	0.0075	0.03%
2		4,741	11.37	0.0075	0.03%
3		4,741	11.37	0.0076	0.03%
4		3,008	13.35	0.0084	0.04%
5		1,805	15.57	0.0123	0.05%
6		1,245	17.18	0.016	0.07%
7		567.8	20.59	0.037	0.16%
8		345.7	22.74	0.066	0.28%
9		193.1	25.27	0.138	0.58%
10		103	27.99	0.334	1.40%
11		49.01	31.23	0.7636	3.18%
12		21.82	34.74	1.54	6.42%
13		8.842	38.67	2.961	12.34%
14		3.444	42.76	5.145	21.44%
15		1.525	46.5	8.008	33.37%
16		1.022	48.04	11.246	46.86%

2.3. Processing with DFCWTCNN

The neuron is the basic building block of the artificial neural network to perform its work similar to the human brain, where the inputs are the information that is received from the outside. A layer called the network layer is formed in the transition area from one cell to another, and it is transmitted in the form of a wavelets of (1+1/2) where it contains one or more inputs to pass through the hidden layers. These layers have been linked to the input layer, the hidden layer, and the output layer with new wavelets DFCWT with convolutional neural network training to make the work more accurate and to improve the work to identify or detect objects. Feeding the classifier AlexNet, taking into account the accuracy of the classification to evaluate the performance of the network with the use of the laws represented by the section 2.4.

2.4. The mathematical aspect of network classification DFCWTCNN

The mathematical aspect can be represented in the form of steps. In the first step, the new filter was built from the new discrete wavelets that were identified in section 2.1, and using (5), which represents the new filter that is passed on successive channels, the dimensions of the filter R are 3×3;

$$Dim\, filter = (R, R, Nc) \tag{13}$$

the convolutional mathematical operation of mapping the image with the new filter;

$$W(I,R)_{x,y} = \sum_{x=1}^{N_L} \sum_{y=1}^{N_W} \sum_{N=1}^{N_c} R_{x,y-R} I_{i+x-1,j+y-1,R} \tag{14}$$

$$Dim\big(W(I,R)\big) = \left(\left[\frac{N_L+2P-R}{S}\right]\right) \tag{15}$$

$$S = 1$$

$$(N_L + 2P - R, N_W + 2P - R) \tag{16}$$

the most important basic criteria that were measured to prove the efficiency of the proposed method in this work are three points, accuracy (ACC), sensitivity (SEN) and specificity (SPE).

$$ACC = \frac{NCA}{NC} = \frac{TP+TN}{TP+FN+FP+TN} \tag{17}$$

$$SEN = \frac{NTPA}{NPA} = \frac{TP}{TP+FN} \tag{18}$$

$$SPE = \frac{NTNA}{NNA} = \frac{TN}{TN+FP} \tag{19}$$

NCA: number of correct assessments.
NC: number of assessments.
NTPA: number of true positive assessments.
NPA: number of positive assessments.
NTNA: number of true negative assessments.
NNA: number of negative assessments.
TP: true positive, a malignant image is correctly identified as malignant.
TN: true negative, a benign image is correctly identified as benign.
FP: false positive, a benign image is mistakenly diagnosed as cancerous.
FN: false negative a malignant image.
To calculate the accuracy of accuracy to prove the efficiency of the new filter.

$$c[x,y] = (I,R)[x,y] = \sum_{i}^{N} \sum_{j}^{M} I(i,j) L[y-i, x-j] \tag{20}$$

$$(L) = max(0, L)$$

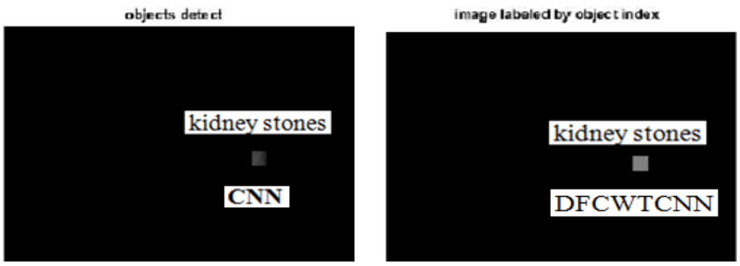
$$Accuracy\, \% = \frac{L_c}{L} \times 100\% \tag{21}$$

2.5. Fast objects identification algorithm DFCWTCNN

The fast algorithm to identify the objects with the new discrete wavelets and connect them to the layers of the convolutional neural network and use the MATLAB program to identify the objects. Algorithm 1, the diseased kidney image will be input to be processed with the new filter DFCWT and then the filter will be connected to the convolutional neural network to build a new network with the new filter DFCWTCNN. Which proven efficiency will be shown by the results that have been reached. This will be shown by Figure 5, that kidney stones will appear clearly.

Algorithm 1. Process with the new filter DFCWT

```
Input color image
Step 1: The grey scale image, which consists of two dimensions, was analysed into the closeness
coefficients, which are concentrated in the first quadrant, LL, and the detail coefficients
in the rest of the quadrants, HL LH HH.
Step 2: Improve the lighting in the image.
Step 3: The 2x2 DCHWT filter begins to remove noise from the input medical image.
Step 4: The image from which the noise has been removed the image is compressed and measured
by PSNR MSE B.P.P and CR image quality standards.
Step 5: Passing the medical image to the convolutional neural network with discrete wavelets
DFCCNNWT using MATLAB program
Vision.CascadeObjectDetector _ Object Detector = vision is created. CascadeObjectDetector,
Out put determination of kidney stones.
```



(a) (b)

Figure 5. To prove the efficiency of the proposed technique, section (a) shows the use of CNN and section and (b) is illustrated using DFCWTCNN

3. RESULTS AND DISCUSSION

To identify kidney stones with classification to achieve DFC WT CNN, Alex Net, and Figure 6 data collection. Shows the accuracy of accuracy with which the required value has been reached. Table 1 shows the steps of the pressing process in successive steps, as the results are recorded in the mentioned table. MSE 4741 error square rate ends 1.022 and PSNR 11.37 to 48.04 which is the result reached for the image quality standards, either after the processing process with the convolutional neural network DFCWTCNN to reach a good value accuracy of 98.84% with 4×4 era and 2 minutes. Figure 5 is divided into two parts to show the difference between using CNN and DFCWTCNN. To prove the efficiency of the proposed technique, Figure 5(a) shows the use of CNN and Figure 5(b) is illustrated using DFCWTCNN and Figure 6 as for the quality standards charts for the results in Figure 7 it is also divided into two parts to show the Figure 7(a) scheme MSE on the resulting image and Figure 7(b) PSNR plot on the resulting image.

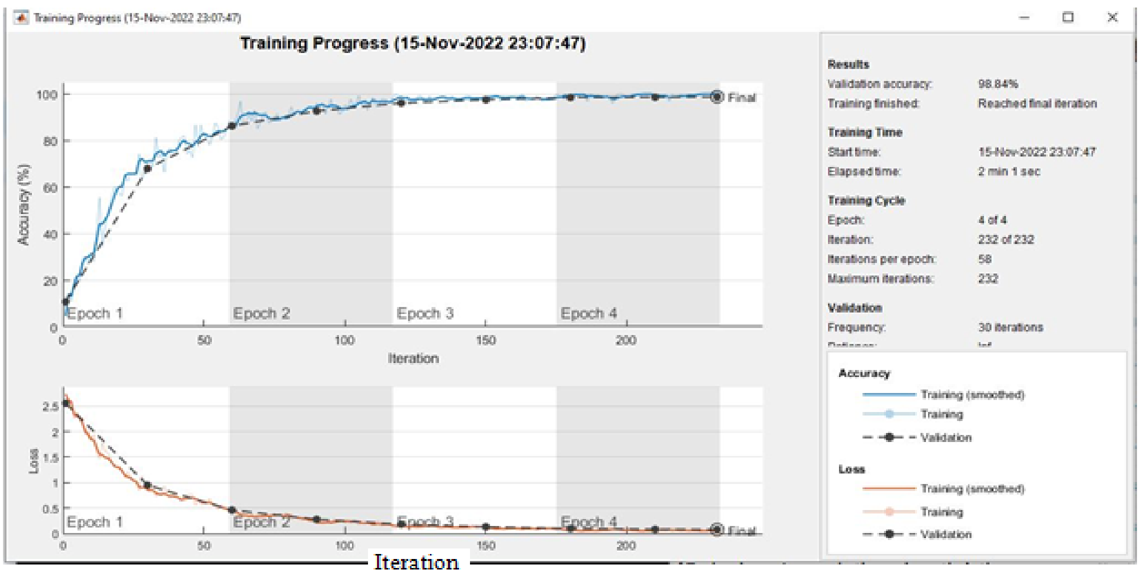
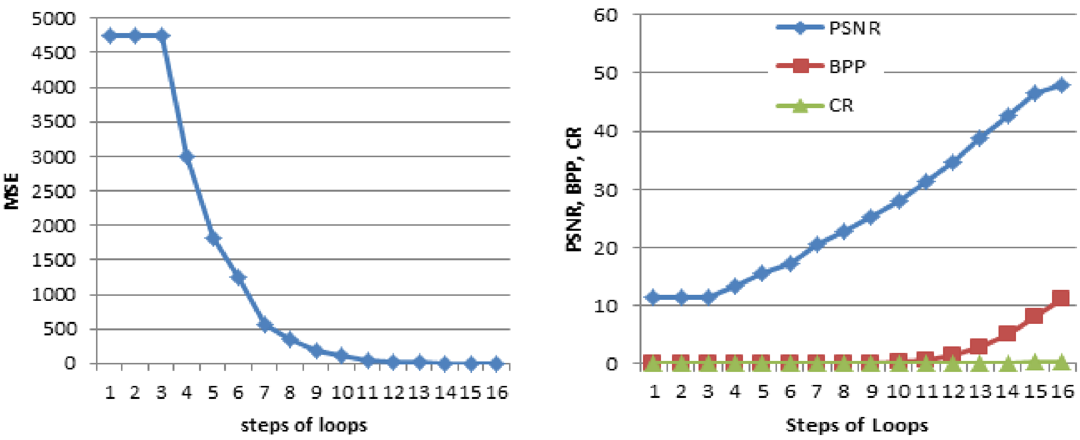


Figure 6. Shows the accuracy of the accuracy with which the desired value was reached



(a) (b)

Figure 7. Divided into two parts to show the section (a) scheme MSE on the resulting image and section and (b) PSNR plot on the resulting image

4. CONCLUSION

Object identification technology in image processing, especially medical images, to improve medical images, and with the advancement of technology and artificial intelligence. In this work, a developed algorithm based on the convolutional neural network was proposed with DFCWT to improve the medical image, especially the image of the kidney affected with stones, to identify the kidney stones. The image was improved by removing the noise from the medical image and then compressing the image to reduce the space occupied by the image data and to prove the quality of the compressed image. The image quality standards were measured the PSNR, MSE, CR, and BPP and by choosing the quadrant that contains the approach coefficients that raised the noise and pressure, after that the convolutional neural network was trained with discrete wavelets to identify the objects with the help of Alex Net network the algorithm DFCWTCNN to reach the accuracy of the value of good 98.84% with 4×4 Epoch and 2 minuets.

ACKNOWLEDGEMENTS

Author thanks. In most cases, sponsor and financial support acknowledgments.

REFERENCES

[1] T. J. Yu, C. P. Lee, K. M. Lim, and S. F. A. Razak, "AI-based targeted advertising system," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 13, no. 2, pp. 787–793, 2019, doi: 10.11591/ijeecs.v13.i2.pp787-793.
[2] M. Ahmed, F. Khalifa, H. E. D. Moustafa, G. A. Saleh, and E. AbdElhalim, "A deep learning based system for accurate diagnosis of brain tumors using T1-w MRI," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 28, no. 2, pp. 1192–1202, 2022, doi: 10.11591/ijeecs.v28.i2.pp1192-1202.
[3] A. G. Diab, N. Fayez, and M. M. El-Seddek, "Accurate skin cancer diagnosis based on convolutional neural networks," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 3, pp. 1429–1441, 2022, doi: 10.11591/ijeecs.v25.i3.pp1429-1441.
[4] S. Bekhet, A. M. Alghamdi, and I. Taj-Eddin, "Gender recognition from unconstrained selfie images: a convolutional neural network approach," *International Journal of Electrical and Computer Engineering*, vol. 12, no. 2, pp. 2066–2078, 2022, doi: 10.11591/ijece.v12i2.pp2066-2078.
[5] A. M. Al-Khafagy, S. R. Hashim, and R. A. Enad, "A unique deep-learning-based model with chest X-ray image for diagnosing COVID-19," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 28, no. 2, pp. 1147–1154, 2022, doi: 10.11591/ijeecs.v28.i2.pp1147-1154.
[6] S. A. Bustin, "Absolute quantification of mrna using real-time reverse transcription polymerase chain reaction assays," *Journal of Molecular Endocrinology*, vol. 25, no. 2, pp. 169–193, 2000, doi: 10.1677/jme.0.0250169.
[7] S. L. A. Al-Galib, A. A. Abdulrahman, and F. S. T. Al-Azawi, "Face detection for color image based on MATLAB," *Journal of Physics: Conference Series*, vol. 1879, no. 2, p. 22129, 2021, doi: 10.1088/1742-6596/1879/2/022129.
[8] S. N. Shihab and M. N. M. Ali, "Collocation orthonormal bernstein polynomials method for solving integral equations," *Eng. &Tech.Journal*, vol. 33, no. 8, pp. 1493–1502, 2015.
[9] A. A. Abdulrahman and F. S. Tahir, "Face recognition using enhancement discrete wavelet transform based on MATLAB," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 23, no. 2, pp. 1128–1136, 2021, doi: 10.11591/ijeecs.v23.i2.pp1128-1136.
[10] A. D. Indriyanti, D. R. Prehanto, and T. Z. Vitadiar, "K-means method for clustering learning classes," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 22, no. 2, p. 835, 2021, doi: 10.11591/ijeecs.v22.i2.pp835-841.

[11] S. L. Galib, F. S. Tahir, and A. A. Abdulrahman, "Detection face parts in image using neural network based on MATLAB," *Engineering and Technology Journal*, vol. 39, no. 1B, pp. 159–164, 2021, doi: 10.30684/etj.v39i1b.1944.

[12] A. A. Abdulrahman, M. Rasheed, and S. Shihab, "The analytic of image processing smoothing spaces using wavelet," *Journal of Physics: Conference Series*, vol. 1879, no. 2, p. 22118, 2021, doi: 10.1088/1742-6596/1879/2/022118.

[13] S. A. Mohammed, A. A. Abdulrahman, and F. S. Tahir, "Emotions students' faces recognition using hybrid deep learning and discrete chebyshev wavelet transformations," *International Journal of Mathematics and Computer Science*, vol. 17, no. 3, pp. 1405–1417, 2022.

[14] A. M. Abduldaim, A. A. Abdulrahman, and F. S. Tahir, "The effectiveness of discrete hermite wavelet filters technique in digital image watermarking," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 25, no. 3, pp. 1392–1399, 2022, doi: 10.11591/ijeecs.v25.i3.pp1392-1399.

[15] Z. K. Alabacy and A. A. Majeed, "The fear effect on a food chain prey-predator model incorporating a prey refuge and harvesting," *Journal of Physics: Conference Series*, vol. 1804, no. 1, p. 12077, 2021, doi: 10.1088/1742-6596/1804/1/012077.

[16] S. Khlil, H. Al-Khazraji, and Z. Alabacy, "Solving assembly production line balancing problem using greedy heuristic method," *IOP Conference Series: Materials Science and Engineering*, vol. 745, no. 1, p. 12068, 2020, doi: 10.1088/1757-899X/745/1/012068.

[17] H. Al-Khazraji, S. Khlil, and Z. Alabacy, "Industrial picking and packing problem: logistic management for products expedition," *Journal of Mechanical Engineering Research and Developments*, vol. 43, no. 2, pp. 74–80, 2020.

[18] S. Khlil, H. Alkhazraji, and Z. Alabacy, "Investagation of the process capability of water pump plastic cover manufacturing," *International Journal of Mechanical Engineering and Technology*, vol. 9, no. 11, pp. 349–359, 2018.

[19] Z. Sufyanu, F. S. Mohamad, A. A. Yusuf, and M. B. Mamat, "Enhanced face recognition using discrete cosine transform," *Engineering Letters*, vol. 24, no. 1. pp. 52–61, 2016.

[20] I. M. Alatawi and N. E. Mohamed, "Face recognition system approach based on neural networks and discrete wavelet transform," *International Journal of Computer Science and Mobile Computing*, vol. 9, no. 9, pp. 1–21, 2020, doi: 10.47760/ijcsmc.2020.v09i09.001.

[21] F. N. J. Nagi, S. K. Ahmed, "A MATLAB based face recognition system using image processing and neural networks," Faculty of Electrical Engineering, UiTM Shah Alam, Malaysia, 2008.

[22] S. Hassairi, R. Ejbali, and M. Zaied, "A deep convolutional neural wavelet network to supervised Arabic letter image classification," *International Conference on Intelligent Systems Design and Applications, ISDA*, vol. 2016-June. IEEE, pp. 207–212, 2016, doi: 10.1109/ISDA.2015.7489226.

[23] A. C. Roy, M. K. Hossen, and D. Nag, "License plate detection and character recognition system for commercial vehicles based on morphological approach and template matching," *2016 3rd International Conference on Electrical Engineering and Information and Communication Technology, iCEEiCT 2016*. IEEE, 2017, doi: 10.1109/CEEICT.2016.7873098.

[24] G. R. Gonçalves, S. P. G. da Silva, D. Menotti, and W. R. Schwartz, "Benchmark for license plate character segmentation," *Journal of Electronic Imaging*, vol. 25, no. 5, p. 053034, 2016, doi: 10.1117/1.jei.25.5.053034.

[25] B. Shi, X. Bai, and C. Yao, "An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 39, no. 11, pp. 2298–2304, 2017, doi: 10.1109/TPAMI.2016.2646371.

[26] Hendry and R. C. Chen, "Automatic license plate recognition via sliding-window darknet-YOLO deep learning," *Image and Vision Computing*, vol. 87, pp. 47–56, 2019, doi: 10.1016/j.imavis.2019.04.007.

[27] F. Zhan and S. Lu, "ESIR: End-to-end scene text recognition via iterative image rectification," *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, vol. 2019-June. IEEE, pp. 2054–2063, 2019, doi: 10.1109/CVPR.2019.00216.

[28] O. Bulan, V. Kozitsky, P. Ramesh, and M. Shreve, "Segmentation- and annotation-free license plate recognition with deep localization and failure identification," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 9, pp. 2351–2363, 2017, doi: 10.1109/TITS.2016.2639020.

[29] C. Henry, S. Y. Ahn, and S. W. Lee, "Multinational license plate recognition using generalized character sequence detection," *IEEE Access*, vol. 8, pp. 35185–35199, 2020, doi: 10.1109/ACCESS.2020.2974973.

[30] H. Seibel, S. Goldenstein, and A. Rocha, "Eyes on the target: super-resolution and license-plate recognition in low-quality surveillance videos," *IEEE Access*, vol. 5, pp. 20020–20035, 2017, doi: 10.1109/ACCESS.2017.2737418.

[31] P. Venkateswari, E. J. Steffy, and D. N. Muthukumaran, "License plate cognizance by ocular character perception'," *International Research Journal of Engineering and Technology*, vol. 5, no. 2, pp. 536–542, 2018.

[32] R. Panahi and I. Gholampour, "Accurate detection and recognition of dirty vehicle plate numbers for high-speed applications," *IEEE Transactions on Intelligent Transportation Systems*, vol. 18, no. 4, pp. 767–779, 2017, doi: 10.1109/TITS.2016.2586520.

[33] F. S. Tahir and A. A. Abdulrahman, "The effectiveness of the Hermite wavelet discrete filter technique in modify a convolutional neural network for person identification," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 31, no. 1, pp. 290–298, Jul. 2023, doi: 10.11591/ijeecs.v31.i1.pp290-298.

[34] A. A. Abdulrahman and F. S. Tahir, "Distinguishing license plate numbers using discrete wavelet transform technology based deep learning," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 30, no. 3, pp. 1771–1776, Jun. 2023, doi: 10.11591/ijeecs.v30.i3.pp1771-1776.

[35] M. A. Mustafa, L. A. A. Hadi, and A. A. Abdulrahman, "New algorithm based on deep learning for number recognition," *International Journal of Mathematics and Computer Science*, vol. 18, no. 3, pp. 429–438, 2023.

[36] Z. Mahmood, O. Haneef, N. Muhammad, and S. Khattak, "Towards a fully automated car parking system," *IET Intelligent Transport Systems*, vol. 13, no. 2, pp. 252–259, 2019, doi: 10.1049/iet-its.2018.5021.

[37] G. S. Hsu, J. C. Chen, and Y. Z. Chung, "Application-oriented license plate recognition," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 2, pp. 552–561, 2013, doi: 10.1109/TVT.2012.2226218.

[38] H. M. Heydari, "Numerical solution of the one-dimensional heat equation by using chebyshev wavelets method," *Journal of Applied & Computational Mathematics*, vol. 01, no. 06, 2012, doi: 10.4172/2168-9679.1000122.

[39] H. Khalajzadeh, M. Mansouri, and M. Teshnehlab, "Hierarchical structure based convolutional neural network for face recognition," *International Journal of Computational Intelligence and Applications*, vol. 12, no. 3, p. 1350018, 2013, doi: 10.1142/S1469026813500181.

[40] S. Bekhet and H. Alahmer, "A robust deep learning approach for glasses detection in non-standard facial images," *IET Biometrics*, vol. 10, no. 1, pp. 74–86, 2021, doi: 10.1049/bme2.12004.

BIOGRAPHIES OF AUTHORS

Fouad Shaker Tahir associate professor, department of applied sciences, mathematics and computer applications branch, University of Technology, Iraq. He holds a Ph.D. in electrical engineering with a specialization in artificial intelligence algorithms. His research areas are image/signal processing, facial identification, and medical image analysis. He supervised many master's theses and participated in many international conferences such as the third international conference of mathematics and its applications (TICMA2022), the 2nd and 3rd international conference on electromechanical engineering and its applications [ICEMEA2021] and Ibn Al-Haitham 2nd international conference for pure and applied science (IHICPAS)-2020. He has published several papers in the fields of image processing and artificial intelligence such as deep learning. He can be contacted at email: fouad.s.tahir@uotechnology.edu.iq.

Asma Abdulelah Abdulrahman associate professor, department of applied sciences, mathematics and computer applications branch, University of Technology, Iraq. She holds a Ph.D. in applied mathematics with a specialization in image processing. Her research areas are image/signal processing, facial identification, and medical image analysis. She supervised many master's theses and participated in many international conferences such as the third international conference of mathematics and its applications (TICMA2022), the 2nd international conference on electromechanical engineering and its applications [ICEMEA2021], Ibn Al-Haitham 2nd international conference for pure and applied science (IHICPAS)-2020. She has published several papers in the fields of image processing and artificial intelligence such as deep learning. She can be contacted at email: asma.a.abdulrahman@uotechnology.edu.iq.