Uluslararası İleri Doğa Bilimleri ve Mühendislik Araştırmaları Dergisi
Sayı 7, S. 38-42, 4, 2023

Araştırma Makalesi

https://as-proceeding.com/index.php/ijanser
ISSN: 2980-0811

International Journal of Advanced Natural Sciences and Engineering Researches
Volume 7, pp. 38-42, 4, 2023

Research Article

KIDNEY STONE DETECTION AND CLASSIFICATION BASED ON DEEP LEARNING APPROACH

Musa Genemo*

[1]*Computer Engineering, Gumushane University, Turkey*

*(musa.ju2002@gmail.com) *Email of the corresponding author*

(Received: 8 April 2023, Accepted: 24 April 2023)

(DOI: 10.59287/ijanser.2023.7.4.545)

(1st International Conference on Scientific and Innovative Studies ICSIS 2023, April 18-20, 2023)

ATIF/REFERENCE: Genemo, M. (2023). Kidney Stone Detection and Classification Based On Deep Learning Approach. *International Journal of Advanced Natural Sciences and Engineering Researches*, 7(4), 38-42

Abstract – Kidney stones are the most common disease, resulting in so many deaths. Early kidney stone detection is essential for minimizing death rates. Early detection and treatment are crucial in the fight against kidney stones. Applying machine learning techniques reduces the workload on physicians while reducing risk and improving diagnostic accuracy. We proposed detection methods in this work that can recognize kidney stones in endoscopy images. For the identification and classification of kidney stones, we suggested five 3D-CNN models. The first three models are used to detect kidney stones; each model has an eight-layer convolutional neural network (CNN-8), while the final two models use a six-layer convolutional neural network (CNN-6) to classify kidney stones. A novel dataset of 1000 images has been collected from various hospitals in Ethiopia. A training set of 0.8 and a testing set of 0.2 were formed from the dataset. The accuracy scores for the 3D-CNN models were 0.985. The novel models produced encouraging outcomes. We think it can address the issues we have had.

Keywords –Classification, Deep Learning, Kidney Stone, Image Processing

I. INTRODUCTION

The kidney is the most important organ part of human health. As of 2020, CKD impacted nearly 37 million adults, and millions more are at greater risk [1]. Additionally, kidney stones are not limited to a particular age limit and may occur at any stage in life.

The prevalence of kidney stones is increasing. According to the Ethiopian public health Association hundreds of thousands of visits to dialysis services, and kidney implants. Unenhanced computed tomography (CT) allows one to make a precise and rapid diagnosis, and clinical history could suggest kidney stone disease [2]. The aforementioned advantages have boosted CT usage for probable urolithiasis [3,4], yet they additionally led to imaging volume rise, turnaround times extend, the responsibilities of radiologists to increase, and hospital admissions get longer [4].

The probability of coming to the emergency department with a complaint of kidney stones is at a critical level. This number is seen to reach 1,000,000 every year in the US only, additionally, this number has doubled between 1992 and 2009 [5-6]. In this way, the reason for the decision can be questioned and its correctness can be discussed in a better way. Recently, AI-based studies have been performed in many areas such as the treatment process of diseases in the human body [6]. One of the most prevalent health issues is kidney stone disease, however, its frequency varies with the territory. This rate has been observed to range between 1 and 20% in prevalence investigations [7,8].

The quality of life of patients and probable kidney failure might be enhanced via studies on the diagnosis of the illness [9]. To generate an in-depth depiction of classification output, DL acquires feature combinations that correlate to the logical arrangement of data structures. The most common type of AI in healthcare at present is the application of deep learning (DL), which is modeled by convolutional neural networks (CNN) [10,11].

With the goal to build accurate and trustworthy DL models that can support clinicians in the diagnosis of diseases like Covid-19, cardiac arrhythmia, prostate cancer, brain tumor, skin, and breast cancer, a wide range of medical image types, including MRI, CT, and X-ray, have been used [11–17]. In the field of urology, DL techniques are additionally employed for the automatic identification of kidney and ureteral stones Fitri et al. [13, 16, 18, 19, 20, 21].

The rest of this paper is organized as follows. In Section 2, related research based on segmentation and detection for the diagnosis of kidney stones has been presented. In Section 3, the utilized methodologies have been detailed. In Section 4, obtained results have been discussed. In Section 5, concluding remarks have been presented.

II. Materials and Method

In this section, the suggested approach is explained in this Section with comprehensive modeling and explanation. The utilized methodology in the study is presented under the section data set presented below.

A. Datasets

This work incorporates novel data formed from images and text "metadata" obtained from a few Ethiopian hospitals. The primary objective of this article is to the image data. Although the dataset provides several images from different perspectives for each patient, the broad range of images helps in arriving at an accurate determination. Furthermore, clinical textual data support our results and aid in understanding the meaning of the collected imagery. Numerous investigations can be conducted with these data alone. a total of 10,000 images of kidney stones in the dataset that was compiled. Images are supplied in (DICOM) format, which is recognized as the most popular format for the exchange and transmission of medical images. A CT scan with and without contrast material was among the data collected. Figure 1 exhibits an accurate CT from the collection of images with and without contrast.

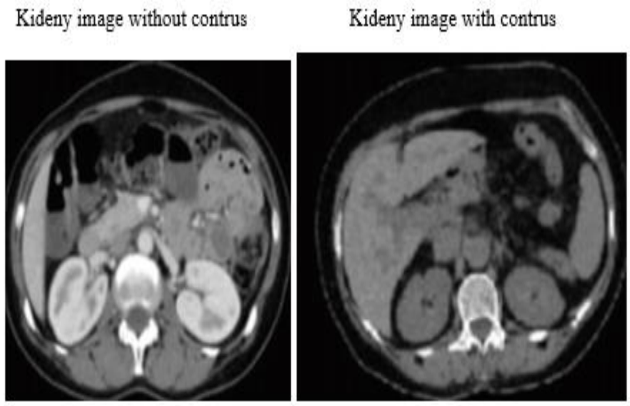

Fig. 1 an analysis of the dataset's data.

Since this data set was used in the image classification task, it does not contain any masks. Therefore, after the high image resolution images were selected in this data set, the labelling process was carried out in this research. Make Sense, which is a web-based image annotation tool was used in the labelling step.

B. Detection Algorithms

In this study, 3D-CNN was used to compare the performances in the detection of kidney stones. 3D-CNN architecture designs instead of selecting some regions in the image, it detects regions in the image and applies a neural network to the entire image to draw bounding boxes around it. 3D-CNN architecture designs area single deep convolutional neural network which is the dividing the input image into grids. The architecture designs have an associated vector that reports whether there is any desired object in that grid. On the other hand, since these architectural designs are a progressive model, their learning improves over time and gives more accurate results.

We carefully examined the quality of the images to reduce the possible errors and risks. For the sake of having a cleaned dataset, we also used the OpenRefine tool and Tableau during the phase of preprocessing. Likewise, we transformed the image format utilizing a DICOM converter, and for each patient, we chose 90 kidney images from an extensive range of dimensions.

The training phase for 3D-CNN architecture designs is as follows: Adam optimizer was used for weights updates, cross-entropy was used as loss function, and learning rate was selected as 1e-3. 3D-CNN architecture designs were trained along 200 epochs while the batch size was set as 6. All experiments were implemented in Google Colab integrated development by using NVIDIA. We also used to explain Artificial intelligence (xAI). Employing this application is mainly carried out so to save time.

III. RESULTS

The approach and comprehensive description of the experiments undertaken are described in this section. The proposed models have been put into practice by employing the Python programming language on Colab. Tensorflow, Keras, SKlearn, Optimizer, and Backend are libraries. Additionally, for processing images and image augmenting, we have utilized several Python tools, such as OpenCV2. The machine that was used for every investigation has a Python 3 Google Compute Engine backend (GPU), 0.80 GB of RAM, 12.69 GB of RAM, and 38.73 GB of hard drive space. The settings of the parameters for our experiment are shown in Table 12.

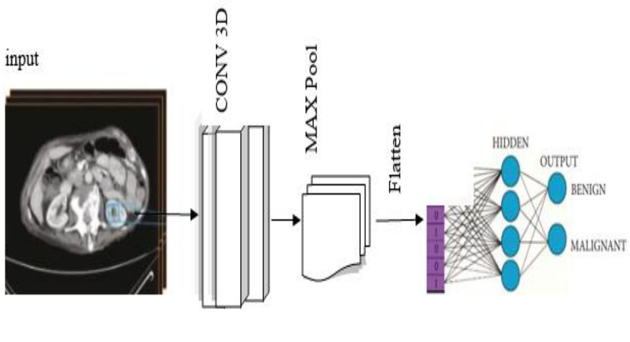

Fig. 2 Proposed Model

Table 1 represents the results obtained by using the 3D-CNN. The mAP50 of 0.982, precision of 0.941, sensitivity of, and F1 score of 0.974values were achieved.

Table 1. Example of a table

Class	3D-CNN	PRE (%)	RSTV (%)	F1-S (%)	Accuracy
Kidney	0.982	0.941	1	0.974	0.991
Kidney stone	0.985	0.983	0.980	0.981	0.985

The training period for the model took 5 hours. We used the confusion matrix to analyse our networks employing the pre-processed dataset. We used F-score metrics, which are decided by the test phase's precision and recall. You'll find more details about metrics for evaluation under.

The training period for the model took 5 hours. We used the confusion matrix to analyse our networks employing the pre-processed dataset. We used F-score metrics, which are decided by the test phase's precision and recall. You'll find more details about metrics for evaluation under.

i. True Positive (TP): It shows the correctly anticipated positive values, signifying that both the actual and shown values of the class are correct.
ii. True Negative (TN): It presents the correctly estimated negative values, so both the real class value and the expected class value are negative.
iii. False Positive (FP): It happens if the expected class is true, but the actual class is false.
iv. False Negative (FN: This happens if the expected class is incorrect, but the actual class is correct.
v. Accuracy: The quantity of accurate predictions acts as a performance indicator.
vi. Accuracy: TP + TN/TP + FP + FN + TN).
vii. Precision: The percentage of successfully predicted events.
viii. positive observations to the total predicted positive observations (Precision: TP/TP + FP).
ix. Recall (sensitivity): It quantifies the percentage of accurately predicted favorable observations to all observations made in the actual class (Recall: TP/TP + FN).

Whereas remembering measures the amount of truly relevant results returned, precision evaluates the relevance of the findings.

IV. DISCUSSION

The proposed methodology and the 2D-CNNs have produced successful results in contrast to earlier efforts. This is the first study to use CT scans for kidney patients to detect and categorize kidney stones based on new data. This research can aid radiologists and doctors in determining the most effective therapy for kidney stone patients. According to the information in Table 2, which compares our anticipated work with earlier research, our study is the first to have used more extensive CT scan data. Additionally, it has done better than previous attempts in terms of accuracy, achieving 97% for kidney stone recognition and 92% for kidney stone labeling.

Table 2. Accuracy results achieved by ResNet50 model.

Class	MAP50	PRE (%)	F1-S (%)	Accuracy
Normal	0.91	0.92	0.0.95	0.95
Kidney stone	0.901	0.887	0.878	0.942

In this work, we presented an entirely novel classification and diagnosis system for kidney stones. Four approaches are used in this research. To analyze the patient's state with kidney stone damage and localize the kidney stone size, 3D-CNN models were used. Using training and testing techniques, the features retrieved from endoscopic images help identify the image class (Normal/kidney stone). The outcomes revealed the effectiveness of our recommended 3D-CNN models for our novel dataset, with a scoring accuracy of 0.98.

This study experienced several challenges, which can be summed up in a few ways: the manual data collection process, image segmentation and image conversion from DICOM to JPEG, image selection, text data building, data labeling, and missing data. when we came into technical issues and needed to re-collect data for some patients; overfitting issues; and the need for high-performance servers.

V. CONCLUSION

In this study, endoscopy images collected from different hospitals are used to classify patients and healthy individuals implementing deep learning approaches. By using these methods, a 3D-CNN is proposed in a shorter time that enables the diagnosis of images that the specialist doctor has difficulty diagnosing we used five 3D-CNN in which the first three models are used for the detection of kidney stones and the last two models with six layers each used for labeling of the kidney as kidney stones and health kidney.

The development of novel datasets and the implementation of a new model can be summed up as the key contributions of this study. Likewise, the results of the models may mitigate the possibility of a false positive, Latency, and the doctor's burden. Also, improving the current level of medical treatment and early exploration can alter the trajectory of the disease and prolong the patient's life.

Our subsequent research will concentrate on further enhancing kidney stone detection performance and pinpoint extraction. We also include some features that can diagnose and classify kidney cancer in our feature works. We need an in-depth examination of this new data with the goal to come up with a solid benchmark for the accurate diagnosis of kidney stone detection using video.

DECLARATION OF INTEREST

There is no relevant conflict of interest.

REFERENCES

[1] Khan, P. F., Reddy, M. R., Samatha, K., Chowdary, R. A., & Rao, P. P. (2021). Predictive Analytics Of Chronic Kidney Disease By Using Machine Learning

[2] Xiao, J., Ding, R., Xu, X., Guan, H., Feng, X., Sun, T., ... & Ye, Z. (2019). Comparison and development of machine learning tools in the prediction of chronic kidney disease progression. Journal of translational medicine, 17(1), 1-13.

[3] Qin, J., Chen, L., Liu, Y., Liu, C., Feng, C., & Chen, B. (2019). A machine learning methodology for diagnosing chronic kidney disease. IEEE Access, 8, 20991-21002

[4] Shafi, N., Bukhari, F., Iqbal, W., Almustafa, K. M., Asif, M., & Nawaz, Z. (2020). Cleft prediction before birth using deep neural network. Health Informatics Journal,1(18) 1460458220911789.

[5] Sharma, S., & Parmar, M. (2020). Heart Diseases Prediction using Deep Learning Neural Network Model. International Journal of Innovative Technology and Exploring Engineering (IJITEE), 9(3).

[6] Fwu, C. W., Eggers, P. W., Kimmel, P. L., Kusek, J. W., & Kirkali, Z. (2013). Emergency department visits, use of imaging, and drugs for urolithiasis have increased in the United States. Kidney International, 83(3), 479–486.

[7] Lin, Z., Cui, Y., Liu, J., Sun, Z., Ma, S., Zhang, X., & Wang, X. (2021). 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. European Radiology, 31(7), 5021–5031.

[8] C. Türk, A. Petˇrík, K. Sarica, C. Seitz, A. Skolarikos, M. Straub, et al., EAU guidelines on diagnosis and conservative management of urolithiasis, Eur. Urol. 69 (2016) 468–474.

[9] A. Chewcharat, G. Curhan, Trends in the Prevalence of Kidney Stones in the United States from 2007 to 2016, Urolithiasis, 2020.

[10] U. Özkaya, Ş. Öztürk, Barstugan, M. Coronavirus (COVID-19) classification using deep features fusion and ranking technique. Big Data Analytics and Artificial Intelligence Against COVID-19: Innovation Vision and Approach, (2020) 281-295.

[11] Jisu, H., Bo-Yong, P., Hyunjin, P.: Convolutional neural network classifier for distinguishing Barrett's esophagus and neoplasia endomicroscopy images.

[12] W. Brisbane, M.R. Bailey, M.D. Sorensen, An overview of kidney stone imaging techniques, Nat. Rev. Urol. 13 (2016) 654.

[13] M.H. Hesamian, W. Jia, X. He, P. Kennedy, Deep learning techniques for medical image segmentation: achievements and challenges, J. Digit. Imag. 32 (4) (2019) 582–596.

[14] H.R. Roth, C. Shen, H. Oda, M. Oda, Y. Hayashi, K. Misawa, K. Mori, Deep learning and its application to medical image segmentation, Med. imaging Technol. 36 (2) (2018) 63–71.

[15] Ş. Öztürk, U. Özkaya & M. Barstuğan, Classification of Coronavirus (COVID-19) from X-ray and CT images using shrunken features. International Journal of Imaging Systems and Technology, (2021) 31(1), 5-15.

[16] T. Ozturk, M. Talo, E.A. Yildirim, U.B. Baloglu, O. Yildirim, U.R. Acharya, Automated detection of COVID-19 cases using deep neural networks with X-ray images, Comput. Biol. Med. (2020) 103792.

[17] O. Kott, D. Linsley, A. Amin, A. Karagounis, C. Jeffers, D. Golijanin, et al., Development of a deep learning algorithm for the histopathologic diagnosis and Gleason grading of prostate cancer biopsies: a pilot study, Eur. Urol. Focus 7 (2) (2019) 347–351.

[18] R. Kijowski, F. Liu, F. Caliva, V. Pedoia, Deep learning for lesion detection, progression, and prediction of musculoskeletal disease, J. Magn. Reson. Imag. 52 (6) (2020) 1607–1619. [18]

[19] O. Yildirim, M. Talo, E.J. Ciaccio, R. San Tan, U.R. Acharya, Accurate deep neural network model to detect cardiac arrhythmia on more than 10,000 individual subject ECG records, Comput. Methods Progr. Biomed. 197 (2020) 105740.

[20] Dheir, I.M. and S.S.J.I.J.o.A.E.R. Abu-Naser, Classification of Anomalies in

[21] Gastrointestinal Tract Using Deep Learning. 2022. 6(3)

[22] Khan, M.A., et al., Multiclass Stomach Diseases Classification Using Deep Learning Features Optimization. 2021.

[23] Sharma, S., & Parmar, M. (2020). Heart Diseases Prediction using Deep Learning Neural Network Model. International Journal of Innovative Technology and Exploring Engineering (IJITEE), 9(3).

[24] Wang, W., Chakraborty, G., & Chakraborty, B. (2021). Predicting the risk of chronic kidney disease (ckd) using machine learning algorithm. Applied Sciences, 11(1), 202.

[25] M. R. Ghalib, S. Bhatnagar, S. Jayapoorani, and U. Pande, "Artificial neural network-based detection of renal tumors using ct scan image processing,"

[26] International Journal of Engineering & Technology, vol. 2, no. 1, pp. 28–35, 2014.