



Employing Advanced Deep Learning Technology for the Detection of Kidney Stones in Unenhanced Computed Tomography (CT) Imaging: A Model-Based Approach

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ABSTRACT

Kidney stones are currently considered a very common disease and recent studies have shown a tendency for the incidence of this disease to increase in recent years. The disease is recognized as a serious threat to the population's health because it is associated with other serious illnesses that can greatly compromise people's quality of life. The development of technologies and strategies aimed at aiding the diagnosis and treatment of this disease has the potential to improve the quality and effectiveness of services provided by health professionals. Diagnosis based on medical images has been one of the main tools for diagnosing kidney stones and Deep Learning techniques have been widely proposed to perform this task. This study proposes a Deep Learning model for detecting kidney stones in computed tomography images. The model was trained with a dataset composed of images obtained from individuals who underwent examinations to analyze diseases in the urinary system. The model achieved an accuracy rate of 96.20% in its predictions and proved to be a suitable tool for treating the problem in question. The results obtained in this study demonstrate the potential of Deep Learning techniques as tools to help improve healthcare procedures related to imaging diagnosis.

1. INTRODUCTION

Kidney stones are considered a very common disease nowadays. According to Lang et al. (2022), the estimated prevalence of this disease ranges from 1% to 13% of the population in different regions of the world. This pathology causes numerous risks to the health of the population because its occurrence is associated with the triggering of other serious diseases that can seriously compromise people's quality of life.

According to Lang et al., (2022) and Zhang et al., (2022) an increasing trend of this disease was found in recent years in a study that analyzed the prevalence of various diseases in 204 countries during the period from 1990 to 2019. It was revealed through this study that more than 115 million cases of the disease occurred globally in 2019 and there were a considerable number of

cases that resulted in death (more than 13 thousand cases). The high rates of occurrence of the disease and the associated criticality reinforce the importance of investing in strategies and technologies to help improve the effectiveness of its diagnosis and treatment.

Medical image analysis is considered one of the main tools for diagnosing and treating kidney stones. According to Iqbal et al. (2023), there is a recognized need to develop computational tools that help doctors and radiologists obtain better accuracy in the analysis and interpretation of medical images, and there is an expectation that such tools can help mitigate the difficulties that may compromise the quality and reliability of the diagnosis. Deep Learning techniques have been widely researched and proposed for medical image

analysis tasks in recent years.

This study proposes a Deep Learning model for detecting kidney stones in computed tomography (CT) images. The objective is to present a model that can be trained with lower consumption of computing resources and achieves satisfactory accuracy rates in its predictions.

2. LITERATURE REVIEW

Kidney stones (also called renal calculi) are mineral structures that form in the urinary system. The medical term used to refer to stones that form in the urinary tract is urinary lithiasis. Stones can form in both kidneys and can vary in size from millimeters to centimeters. According to Alelign and Petros (2018), this pathology has afflicted humanity for millennia and recent studies have shown that its occurrence has increased in recent decades.

This pathology has been considered a serious threat to the health of the population as its development has been associated with the emergence of diseases such as cardiovascular disease, hypertension, diabetes, kidney failure and irreversible loss of kidney function. According to Alelign and Petros (2018), the main symptoms of the presence of kidney stones are: intense renal colic, intense back pain, presence of blood in the urine, urinary infections, blockage of urine flow and dilation of the kidneys (hydronephrosis).

Kidney stones are classified according to their mineral composition. The 4 main types are: calcium stones, struvite stones (magnesium ammonium phosphate), uric acid stones and cystine stones. According to Khan et al., (2019), calcium stones are the most common type and account for around 80% of cases, and cystine stones are the rarest type and account for around 1% of cases.

Diagnosis of kidney stones is carried out through blood tests, urine tests and imaging tests. Urine analysis seeks to check whether there is any abnormality in its PH levels and whether there are signs of infections. Blood analysis seeks to check whether there is any problem in the functioning of the kidneys by analyzing the levels of certain substances such as creatinine, urea, calcium, and uric acid. Image analysis seeks to check whether there are stones in the urinary system and their quantity, size, and location.

According to Brisbane et al., (2019) imaging exams

provide doctors with confidence in the accuracy of the diagnosis because they allow them to confirm whether the symptoms observed in the patient are caused by the presence of stones or are associated with other pathologies, and they allow them to assess the risks associated with the passage of stones through the channels of the urinary system by measuring their size and mapping their location. The imaging modalities used for diagnosis and treatment of kidney stones are: computed tomography (CT), ultrasonography, radiography, and magnetic resonance imaging (MRI). According to Brisbane et al., (2019) each modality has its advantages and limitations, and the choice of the modality to be used may depend on several factors such as the level of accuracy (sensitivity and specificity) desired, financial costs associated with the procedures, and patients' tolerance to the ionizing radiation generated by equipment.

CT techniques were introduced in the 1970s and have become a widely used tool in medical diagnosis due to the numerous improvements incorporated in recent decades to improve the resolution and speed of equipment. According to Al-Sharify et al., (2020) and Hussain et al., (2022) CT scanners produce different X-ray images from different angles and such images make it possible to check the states of different tissues and organs of the human body for the diagnosis of different diseases.

CT image analysis has been widely used for the diagnosis of kidney stones as it allows exams to be carried out quickly and non-invasively, and enables high rates of diagnostic accuracy to be achieved thanks to high levels of sensitivity and specificity obtained in the exams. According to Ather et al., (2017) an advantage of CT techniques is that they enable the discovery of different properties of stones such as their size, mineral composition, location and distance between the stone and the skin. This set of information helps to assess the associated risks and plan the treatment to be carried out to eliminate the stones.

The use of Deep Learning techniques to aid medical diagnosis based on images has increased in recent years. Deep Learning models have been proposed to perform pattern recognition and anomaly detection tasks in medical images. Convolutional Neural Networks (CNNs) are a type of Deep Learning model that has received a lot of attention from researchers and has been widely used to

perform image classification tasks. According to Sarvamangala and Kulkarni (2022), CNNs have achieved satisfactory results in analyzing images of various organs of the human body to aid in the diagnosis of various diseases.

The ability of CNNs to automatically extract features is an important characteristic that differentiates them from other types of Machine Learning and Deep Learning models. According to Sarvamangala and Kulkarni, (2021), learning which features are most important for detecting patterns in images is a challenging task in certain problem domains and the ability of CNNs to automatically extract low-level and high-level features from images is crucial to build models that achieve excellent performance in their predictions. Another feature that favors the use of CNNs in comparison to other traditional Neural Network architectures is the weight sharing feature which, according to Alzubaidi et al. [14][15], allows a reduction in the number of trainable network parameters, which reduces model training time and improves the network's learning capacity.

3. METHODS

3.1 Dataset description

The dataset used in this study was made available through research developed by Yildirim et al. (2021). The dataset consists of CT images obtained from 433 individuals who underwent examinations to analyze diseases in the urinary

system at Elazig Fethi Sekin City Hospital (Turkey). The images were acquired without administration of contrast and, for this reason, they are called "unenhanced images" in this study. The images are coronal and include the abdomen, pelvis, and chest. Each image was labeled by two specialists (doctor and radiologist) as "normal" or "with stone." This study used 1500 images from the dataset, with 50% of the images belonging to each label.

3.2 Pre-processing

All images were resized up to the size of the largest image in the dataset (278 x 386 pixels). This standardization is necessary because a prerequisite for CNNs is that all images in the input set must have the same size. The zero-padding technique (edge filling) was used to resize the images. This technique was chosen because, according to Hashemi [17][18], zero-padding does not cause negative effects on the model's accuracy and reduces its training time because the pixels on the edges generated by the padding are considered "zeroed" units that do not generate activation of neighboring units and this avoids the cost of updating network parameters associated with these units [19][20]. Fig. 1 presents 2 examples of images from the dataset. The image on the left shows the CT of a patient diagnosed as "normal" and the image on the right shows the CT of a patient diagnosed as "with stone".

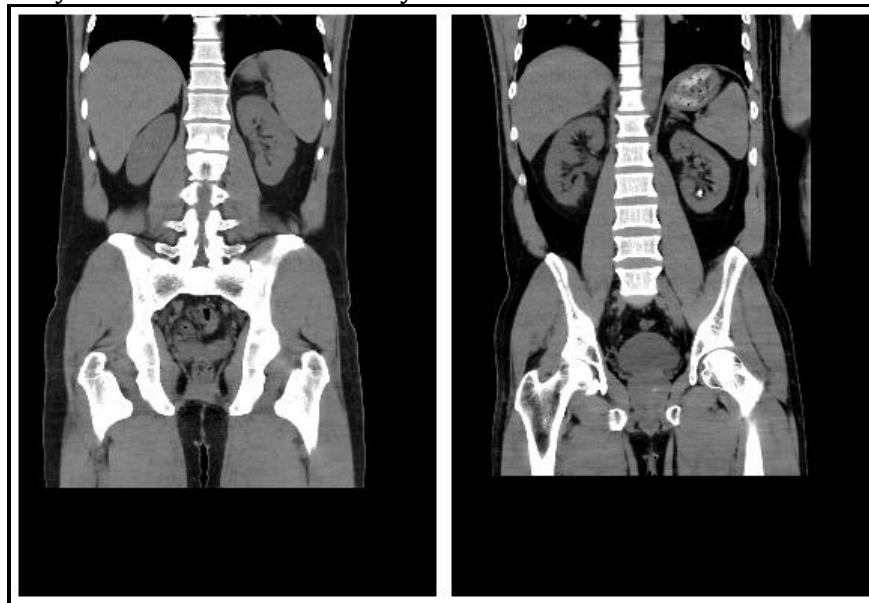


Figure 1. CT with "normal" label in the left image and CT with "stone" label in the right image.

3.3 Model Training

The architecture of the CNN model proposed in this study is shown by Fig. 2. The architecture has 3 Convolutional layers followed by 1 Batch Normalization layer and 1 Max Pooling layer each, 1 Flatten layer, 1 Fully Connected layer followed by

1 Batch Normalization layer, and 1 output layer. Table 1 presents the hyperparameters configuration of each network layer.

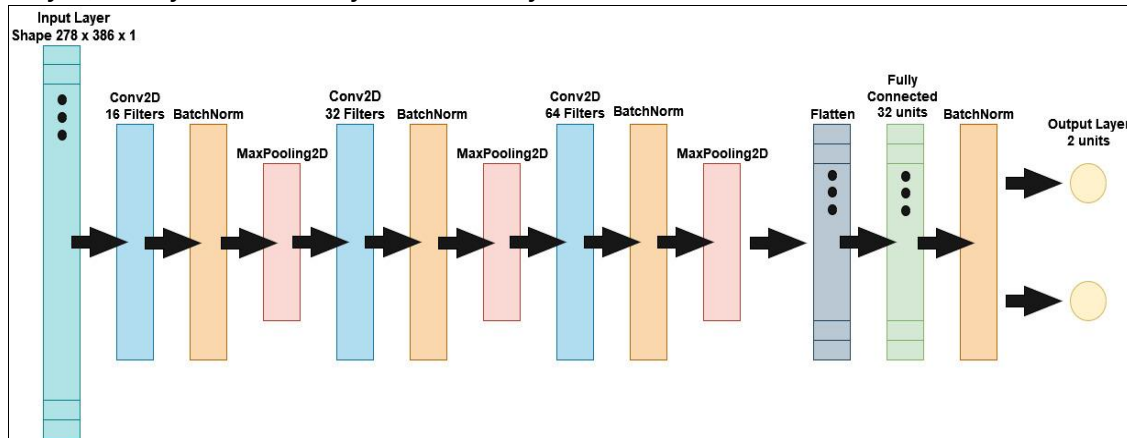


Figure 2. CNN model architecture.

The model was implemented using the Tensorflow framework with the Keras library. Training was performed with a limit of 300 epochs using the Adam optimizer, learning rate of 0.001 and batch size of 32. The cross-validation technique (10

Folds) was used for training with the aim of obtaining better generalization capacity and avoid overfitting and bias.

Table 1. Hyperparameters of each layer.

Layer	Layer type	Filters	Kernel size	Activation	Pooling size	Units
Layer 1	Conv2D	16	3	reLU	-	-
Layer 2	BatchNormalization	-	-	-	-	-
Layer 3	MaxPooling2D	-	-	-	2	-
Layer 4	Conv2D	32	3	reLU	-	-
Layer 5	BatchNormalization	-	-	-	-	-
Layer 6	MaxPooling2D	-	-	-	2	-
Layer 7	Conv2D	64	3	reLU	-	-
Layer 8	BatchNormalization	-	-	-	-	-
Layer 9	MaxPooling2D	-	-	-	2	-
Layer 10	Flatten	-	-	-	-	-
Layer 11	Dense	-	-	reLU	-	32
Layer 12	BatchNormalization	-	-	-	-	-
Layer 13	Dense	-	-	Softmax	-	2

4. RESULTS AND DISCUSSION

The CNN model achieved an average accuracy rate of 96.20% with a standard deviation of 0.0209 in

the test set predictions. When comparing the average accuracy rate of the test set with the average accuracy rate of the training set (96.22%),

it can be seen that the model did not suffer from overfitting and presented a good generalization capacity. Table 2 presents the detailed training metrics (precision, recall and F1-Score). The high rates obtained for these metrics are an indicator that the model's performance was not compromised by false positives or false negatives.

Table 2. CNN model training metrics.

Class	Precision	Recall	F1-Score
0	0.93	1.00	0.96
1	1.00	0.93	0.96

The proposed model uses 3,132,834 trainable parameters, which demonstrates its ability to achieve good performance in dealing with the problem in question while consuming fewer computational resources. Models that achieve a better balance between performance and consumption of computational resources enable training to be carried out in less time and solutions to be developed at a lower cost.

This study, however, is subject to certain limitations. The interpretability difficulties of Neural Network models can make it difficult to understand which images features was considered most relevant by the model to make its conclusions. Future work that makes it possible to obtain better interpretability of the model's conclusions could contribute to a better understanding of how the model recognizes patterns in the analyzed images and why certain images were classified incorrectly.

5. CONCLUSION

The use of computational tools to assist healthcare professionals in analyzing image exams can provide mechanisms to reduce the time needed to carry out diagnoses and the costs related to the procedures. Professionals can use this aid to increase their confidence in the accuracy of the analysis performed and provide patients with a more accurate diagnosis. Providing tools that help minimize the possibility of incorrect or incomplete diagnoses is important in scenarios related to the treatment of diseases considered serious, such as kidney stones.

Deep Learning models, especially Convolutional Neural Networks (CNNs), have proven to be excellent tools for automating pattern recognition tasks in medical images. The CNN model proposed in this study adequately addressed the problem in

question by achieving satisfactory performance in identifying kidney stones in the images contained in the dataset.

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