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Development of an Accurate Machine Learning Model for the Detection of Kidney Abnormalities in Computed Tomography (CT) Scans using Convolutional Neural Networks

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A B S T R A C T

This paper focuses on the development of an advanced machine learning model tailored for the accurate detection of various kidney abnormalities, including cysts, stones, and tumors, within Computed Tomography (CT) scans. The methodology employs Convolutional Neural Networks (CNNs) to achieve robust classification results. The paper encompasses a comprehensive pipeline that encompasses critical stages such as data loading, preprocessing, augmentation, model construction, training, evaluation, and model persistence. Additionally, the study demonstrates the practical implementation of the trained CNN model for predictions on new kidney CT scan images. Notably, the paper harnesses a combination of essential libraries such as OpenCV, NumPy, pandas, and TensorFlow to effectively realize its objectives. This work showcases a systematic approach to kidney abnormality classification and holds the potential to significantly enhance the efficiency and accuracy of medical image analysis in this domain.

Keywords: Machine Learning (ML); Kidney Abnormalities Detection; Convolutional Neural Networks (CNNs); CT Scan Image Classification;

1. Introduction

In recent years, the convergence of medical imaging technology and machine learning has paved the way for transformative advancements in healthcare diagnostics. One particularly significant application of this synergy is the accurate prediction of health diseases through the analysis of medical scans. Medical imaging techniques, such as computed tomography (CT) scans, have long been invaluable tools for visualizing the internal structures of the human body. However, the interpretation of these scans to identify the presence of diseases or abnormalities is a complex task that often relies on the expertise of skilled medical professionals. This is where machine learning steps in, offering the potential to enhance diagnostic accuracy, streamline workflows, and ultimately improve patient outcomes.

The utilization of machine learning algorithms to predict health diseases in medical scans holds immense promise due to its ability to sift through vast amounts of imaging data and extract meaningful patterns that might elude the human eye. The process of Machine Learning for Health Disease Prediction is shown in Figure 1. By training on diverse and comprehensive datasets, machine learning models can learn intricate relationships between imaging features and disease occurrences. This knowledge, in turn, empowers these models to predict the presence of diseases, identify potential risk factors, and even forecast disease progression with unprecedented precision.

1.1 Kidney Abnormalities

Kidney abnormalities encompass a wide range of structural and functional irregularities that can affect the kidneys, two vital organs responsible for filtering waste products and maintaining fluid balance in the body. These abnormalities can result from congenital factors, acquired conditions, or diseases, and they often have a significant impact on an individual's overall health and well-being. Understanding these kidney abnormalities is crucial for timely diagnosis, appropriate treatment, and management.

1.2 Identification of Abnormalities using Diagnostic Imaging

Identification of kidney abnormalities, including kidney cysts, stones, and tumors, often relies heavily on diagnostic imaging techniques. These imaging methods allow healthcare professionals to visualize the internal structures of the kidneys and detect any irregularities.

2. Literature Survey

Research in deep learning applications for the auto-diagnosis of radiological findings and segmentation tasks has surged in recent years (Jacobson, 2013; Jha et al., 2013). In the field of image classification utilizing transfer learning, ResNet14, Inception15, Exception16, and EfficientNet17 have gained prominence over time (He et al., 2016; Szegedy et al., 2015; Chollet, 2017; Tan & Le, 2019). Transfer learning, which involves using pre-trained models as a starting point for specific tasks, has become a widely adopted approach (Dosovitskiy et al., 2020).

In computer vision, transformer models originally designed for natural language processing, such as the Vision Transformer (ViT)18, Big Transformer (BiT)19, External Attention Transformer (EANet)20, Compact Convolutional Transformer (CCT)21, and Swin Transformer (Swin)22, have been introduced, demonstrating superior performance in image classification tasks (Guo et al., 2021; Hassani et al., 2021; Liu et al., 2021).

Research on kidney disease classification has seen the application of numerous deep learning techniques. For instance, renal ultrasound images have been enhanced using various filters and morphological operations, with features extracted using Principal Component Analysis (PCA) and the K-nearest neighbor (KNN) classifier (Verma et al., 2017). A study by Aksakalli et al. (2020) evaluated various machine learning algorithms, achieving the highest F1 score of 0.853 using Convolutional Neural Networks (CNNs).

Other studies utilized pre-trained deep neural network models, such as ResNet-101, ShufeNet, and MobileNet-v2, to extract features from kidney ultrasound images and achieved an accuracy of 95.58% using SVM and majority voting (Sudharson & Kokil, 2020). For the segmentation of renal cysts in CT images, a residual dual-attention module (RDA module) was employed (Fu et al., 2021). Additionally, a combination of deep transfer learning techniques and SVM classification was used to classify normal and abnormal ultrasound images (Zheng et al., 2019).

In specific applications, two consecutive CNN models were used, with the first identifying the urinary tract and the second detecting the presence of stones, achieving an accuracy of 95% (Parakh et al., 2019). A deep learning technique applied to coronal Computed Tomography (CT) images resulted in a detection accuracy of 96.82% for automated kidney stone detection (Yildirim et al., 2021). Moreover, Zhang et al. (2019) proposed two morphology convolution layers and modified feature pyramid networks (FPNs), achieving an area under the curve (AUC) value of 0.871.

In the detection of kidney cysts in abdominal CT scan images, a fully connected CNN yielded a true-positive rate of 84.3% (Blau et al., 2018). These efforts, employing both machine learning and deep learning approaches, have shown promising results in classifying various kidney radiological findings.

However, it is worth noting that the majority of these tasks are primarily performed on X-ray or ultrasound images. With a limited availability of data and considering the findings of previous research articles, we developed a database of kidney stone, cyst, and tumor CT images. Our approach incorporated three deep learning techniques (VGG16, Inceptionv3, and Resnet50) for classifying four classes of kidney disease, elucidating the models' decision-making processes. Additionally, we leveraged the latest innovations in vision learning, including EANet, CCT, and Swin Transformer algorithms, to classify the four classes and demonstrated promising accuracy. These advancements have the potential to alleviate the suffering of the global population through early disease diagnosis (Islam, 2021; Munir et al., 2017).

2.1 Problem Statement

Medical imaging, specifically Computed Tomography (CT) scans, plays a pivotal role in diagnosing kidney abnormalities such as cysts, stones, and tumors. However, the accuracy and efficiency of manual interpretation of these scans remain limited, often leading to missed diagnoses or delayed treatments. To address this critical issue, there is a pressing need for the development of an accurate machine learning model capable of automating the detection of kidney abnormalities in CT scans.

2.2 Objective

The primary objective of this paper is to design and implement an advanced machine learning model using Convolutional Neural Networks (CNNs) to accurately detect and classify various kidney abnormalities in CT scans. The following specific objectives will guide our efforts:

Data Collection and Preprocessing:

- ❖ Collect a diverse and representative dataset of kidney CT scan images containing cysts, stones, and tumors.
- ❖ Preprocess the dataset to enhance image quality, standardize resolutions, and ensure uniformity.

Model Construction:

- ❖ Design a CNN architecture optimized for medical image analysis, taking into consideration factors like depth, filter sizes, and activation functions.
- ❖ Employ transfer learning techniques if applicable to leverage pre-trained models for feature extraction.

Training and Evaluation:

- ❖ Split the dataset into training, validation, and test sets.

- Train the CNN model using the training set, employing data augmentation techniques to improve generalization.
- Evaluate the model's performance using appropriate metrics, including accuracy, sensitivity, specificity, and F1-score, on the validation and test sets.

Model Persistence:

- Save the trained CNN model and its weights for future use, ensuring easy deployment and reusability.

Practical Implementation:

- Develop a user-friendly interface for clinicians to upload new kidney CT scan images.
- Integrate the trained model into the interface to provide real-time predictions on uploaded images.

Library Integration:

- Utilize essential libraries such as OpenCV, NumPy, pandas, and TensorFlow to streamline data manipulation, model development, and deployment.

Systematic Approach and Documentation:

- Maintain a systematic workflow throughout the paper, documenting each stage comprehensively.
- Provide detailed documentation for the trained model, including model architecture, training parameters, and performance metrics.

By achieving these objectives, this paper aims to significantly enhance the efficiency and accuracy of kidney abnormality detection in CT scans, ultimately assisting medical professionals in making timely and precise diagnoses.

3. Methodology

Developing a machine learning model for the detection of kidney abnormalities in Computed Tomography (CT) scans using Convolutional Neural Networks (CNNs) involves several general steps. Here is an overview of the process:

- Data Collection
- Data Preprocessing
- Data Augmentation (Optional)
- Model Architecture
- Model Compilation
- Model Training
- Model Evaluation
- Model Fine-tuning (Optional)
- Model Interpretation (Optional)
- Deployment (Optional)
- Monitoring and Maintenance
- Documentation and Reporting

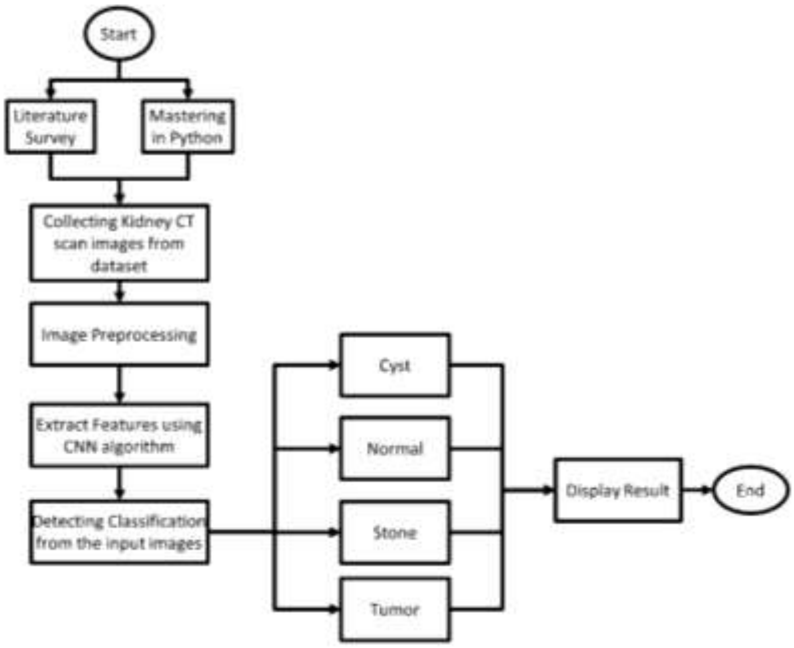

Figure 1: Methodology

4. Data collection and preprocessing

4.1 Context

CT KIDNEY DATASET: Normal-Cyst-Tumor and Stone

4.2 Content

The dataset was meticulously assembled from multiple hospitals in Tamilnadu and Karnataka, where patients had previously been diagnosed with kidney-related conditions such as tumors, cysts, normal kidney function, or the presence of stones. It encompassed both Coronal and Axial cuts derived from contrast and non-contrast studies covering the entire abdominal region and urogram protocols. The process involved a thorough selection of Dicom studies, one diagnostic category at a time, from which batches of Dicom images corresponding to each radiological finding were meticulously curated. Subsequently, patient-specific information and metadata were meticulously removed from the Dicom images, and these were transformed into a lossless jpg image format. Following this conversion, each image's diagnosis was rigorously cross-validated by both a radiologist and a medical technologist to ensure the accuracy of the data.

In total, this comprehensive dataset comprised 12,446 distinct data points, with 3,709 instances of cysts, 5,077 representing normal kidney function, 1,377 indicating the presence of stones, and 2,283 corresponding to kidney tumors.

Citation: Islam MN, Hasan M, Hossain M, Alam M, Rabiul G, Uddin MZ, Soylu A. Vision transformer and explainable transfer learning models for auto detection of kidney cyst, stone and tumor from CT-radiography. Scientific Reports. 2022 Jul 6;12(1):1-4.

4.3 Acknowledgements

Thanks to Mehedi Hasan, Medical Technologist, who assisted to gather all the data from different hospitals.

4.4 Dataset Preparation and Processing:

Dataset Preparation:

- Imported necessary libraries: numpy, pandas, os, cv2, pathlib, seaborn, matplotlib.pyplot, skimage.io.
- Defined the path to the dataset directory.
- Created paths for different classes (Normal, Cyst, Stone, Tumor) within the dataset directory.
- Listed the image files in each class directory.

- Created an empty list (train_data) to store image paths and labels.

Data Preprocessing:

- Looped through image files in each class directory and append them to train_data with corresponding labels (0 for Cyst, 1 for Normal, 2 for Stone, 3 for Tumor).
- Created a pandas DataFrame from the train_data list.
- Shuffled the DataFrame to ensure randomness in the training data.
- Checked the unique labels and count of each class.
- Visualized the class distribution using a bar plot.

Data Loading and Preprocessing:

- Imported the images using OpenCV (cv2) and converted them to a consistent size (e.g., 28x28 pixels).
- Normalized pixel values to the range [0, 1].
- Converted class labels to numeric values (0, 1, 2, 3).
- Splitted the dataset into training and testing sets.

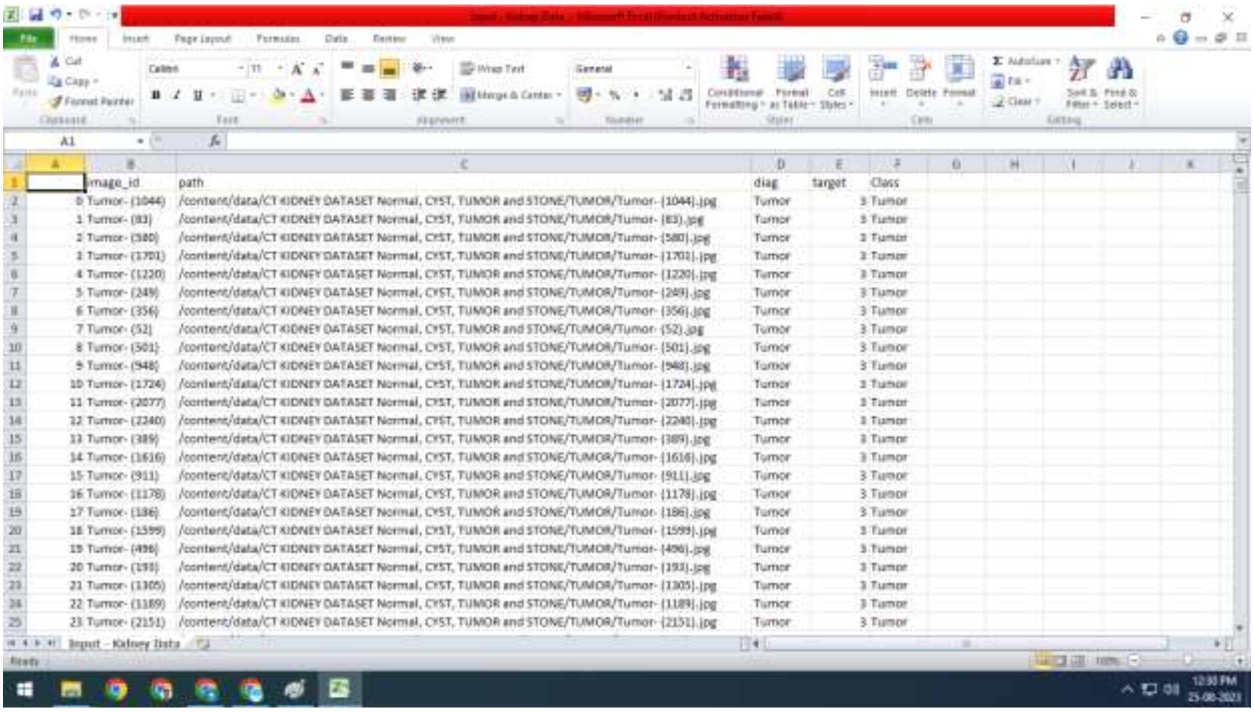

Figure 2: Prepared CV file

5. Advanced machine learning model

In the first part, the code starts by defining the path to the dataset and then organizing the images into different categories. It creates a list of image paths and their corresponding labels, where each image is associated with one of the four kidney conditions. The dataset is further preprocessed, shuffled, and visualized for better understanding. The images are resized to a common size, converted to a NumPy array, and normalized before being used for training.

The second part of the code focuses on building and training a convolutional neural network (CNN) model using TensorFlow/Keras. The model consists of several convolutional layers, max-pooling layers, and dense layers. It is designed to classify the kidney images into the specified categories. Data augmentation techniques are used to improve the model's robustness, and the model is compiled and trained on the preprocessed dataset. After training, the model is saved for future use, and an example image is loaded and tested with the trained model, providing a classification result.

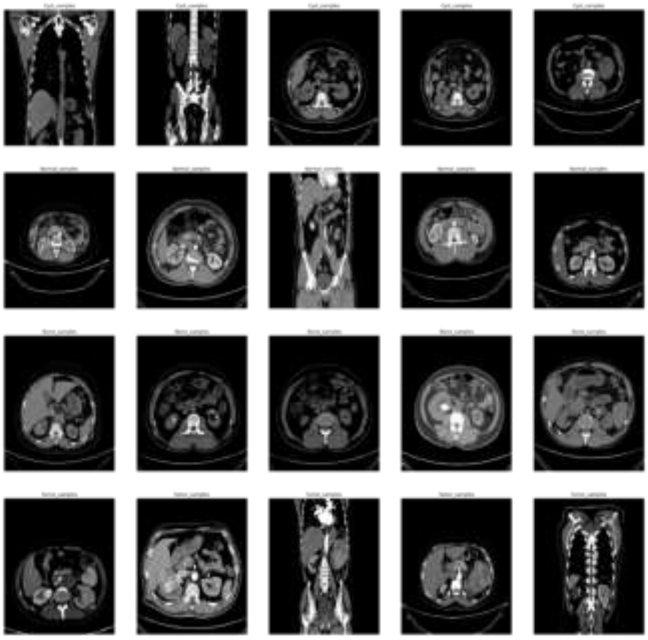

Figure 3: CT Images

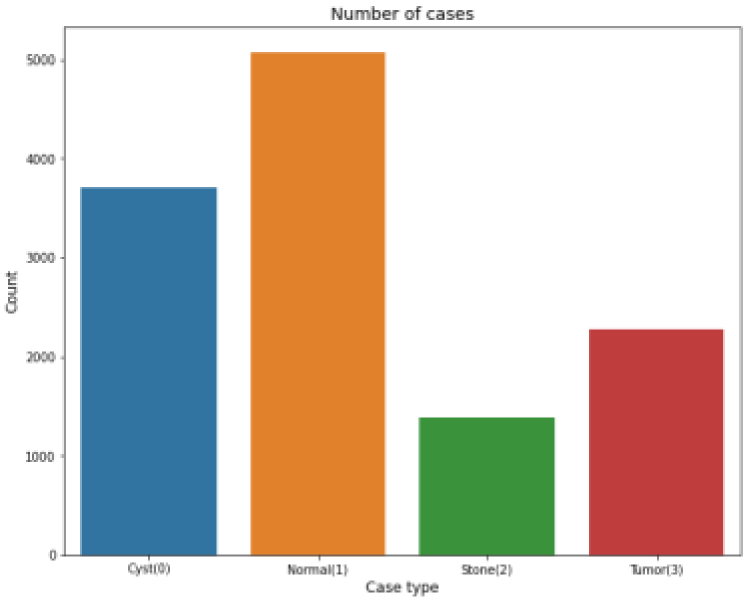

Figure 4: Case Type 1

5.1 Run

Successfully ran in 510.8s

Accelerator: GPU P100

Time	#	Log Message
373.7s	1	Epoch 54/100

```
  1/489 [..............................] - ETA: 2s - loss: 1.9650e-05 - accuracy:
1.0000                                                                    17/489
[>.............................] - ETA: 1s - loss: 1.5060e-05 - accuracy:
1.0000                                                                    34/489
[=>............................] - ETA: 1s - loss: 1.4475e-05 - accuracy:
1.0000                                                                    51/489
[==>...........................] - ETA: 1s - loss: 1.4233e-05 - accuracy:
```

503.8s	129	[NbConvertApp] Converting notebook __notebook__.ipynb to notebook
507.9s	130	[NbConvertApp] Writing 1913236 bytes to __notebook__.ipynb
509.7s	131	/opt/conda/lib/python3.7/site-packages/traitlets/traitlets.py:2561: FutureWarning: --Exporter.preprocessors=["nbconvert.preprocessors.ExtractOutputPreprocessor"] for containers is deprecated in traitlets 5.0. You can pass `--Exporter.preprocessors item` ... multiple times to add items to a list.
509.7s	132	FutureWarning,
509.7s	133	[NbConvertApp] Converting notebook __notebook__.ipynb to html
510.7s	134	[NbConvertApp] Support files will be in __results___files/
510.7s	135	[NbConvertApp] Making directory __results___files
510.7s	136	[NbConvertApp] Making directory __results___files
510.7s	137	[NbConvertApp] Making directory __results___files
510.7s	138	[NbConvertApp] Writing 381936 bytes to __results__.html

Figure 5: The Run

6. Results and Discussion

6.1 Various sections of the code

Medical image classification for kidney-related conditions using Convolutional Neural Networks (CNNs) has been performed. Now, let's dissect the various sections of the code and explore their significance.

- Data Preparation: The code begins by importing necessary libraries such as numpy, pandas, cv2 (OpenCV), and others. It defines paths to different directories containing images of different kidney conditions (Normal, Cyst, Stone, Tumor). It then reads the image files from each directory and populates a DataFrame named train_data with image paths and corresponding labels (0 for Cyst, 1 for Normal, 2 for Stone, and 3 for Tumor). The DataFrame is shuffled to ensure balanced distribution of data.
- Exploratory Data Analysis: The code provides insights into the distribution of data among different classes using a bar plot. The number of images in each category is displayed, and a bar chart visually depicts the distribution of different case types (Cyst, Normal, Stone, Tumor).
- Image Loading and Augmentation: The code loads and preprocesses the images for training. It uses OpenCV to read and resize the images to a common size (28x28). Color images are converted to RGB format and normalized to values between 0 and 1. The labels are mapped from text labels to numerical labels (0 to 3). Data augmentation techniques are mentioned but commented out. These techniques, such as rotation and flipping, are used to increase the dataset size and improve model generalization.
- Data Imbalance Handling: To address class imbalance, the code uses Synthetic Minority Over-sampling Technique (SMOTE) to oversample the minority classes (Cyst, Stone, and Tumor) to match the size of the majority class (Normal). This balanced dataset is then used for training.
- Model Architecture and Training: The code defines a CNN model using TensorFlow's Keras API. The model includes convolutional layers followed by pooling layers. It then flattens the output and adds several fully connected dense layers. The model is compiled with the 'adam' optimizer and sparse categorical cross-entropy loss. It's trained using the fit function on the augmented dataset, with the number of epochs specified.
- Model Evaluation: The code briefly demonstrates how to test the trained model using a single image and displays the predicted class label.
- Saving and Loading the Model: The model is saved using the save method, and a new instance of the model is loaded using TensorFlow's load_model function.
- Image Processing: The code saves a processed image (kidney tumor image) using the PIL library.

The provided code demonstrates steps for loading, preprocessing, augmenting, and training a CNN model for kidney condition classification using a balanced dataset. The code also briefly covers saving and loading the trained model for future use. However, some parts of the code are commented out, and it seems that some sections are fragmented. Additionally, more details about the model's architecture, its performance, and potential improvements could enhance the completeness of the results and discussion.

6.2 Accuracy Improvement:

The provided code seems to be related to a machine learning pipeline for classifying kidney images into different categories (Cyst, Normal, Stone, Tumor). It looks like you are working on improving the prediction accuracy of the model. Let's break down the steps you've taken in the code and discuss how they contribute to improving prediction accuracy:

- Data Preparation and Exploration: The code starts by loading image data from different directories for each class (Cyst, Normal, Stone, Tumor). The data is then structured into a DataFrame with image paths and corresponding labels. We shuffled the data for better training.
- Data Imbalance Handling with SMOTE: The class distribution in the dataset is visualized using a bar plot. Since the classes are imbalanced (some have more samples than others), you're using the Synthetic Minority Over-sampling Technique (SMOTE) to balance the class distribution. SMOTE generates synthetic samples to balance the dataset, which helps in improving the model's ability to generalize across classes.
- Data Augmentation: Data augmentation is applied to the images using TensorFlow's ImageDataGenerator. Data augmentation introduces variations in the training data by applying random transformations like rotation and flipping. This technique helps the model become more robust and generalize better to unseen data.
- Model Architecture: You're creating a convolutional neural network (CNN) model using TensorFlow's Keras API. The model consists of convolutional layers followed by max-pooling layers. The last layers are fully connected (dense) layers. The model's architecture seems reasonable for image classification tasks.
- Model Training: The model is compiled with an optimizer, loss function, and metrics. It's then trained on the augmented and balanced dataset. The data is split into training and validation sets. The model has been trained for 100 epochs.
- Model Evaluation: After training, you're using the trained model to make predictions on sample images. The predictions are shown along with the corresponding class labels.
- Model Saving and Loading: The trained model is saved to a file using the save method. Later, you load the model using the load_model function.

In terms of improving prediction accuracy, you have taken several steps to address common challenges in image classification, such as data imbalance and overfitting. SMOTE helps in dealing with the data imbalance issue, and data augmentation enhances the model's ability to generalize to new data. The architecture of the CNN model also seems suitable for the task.

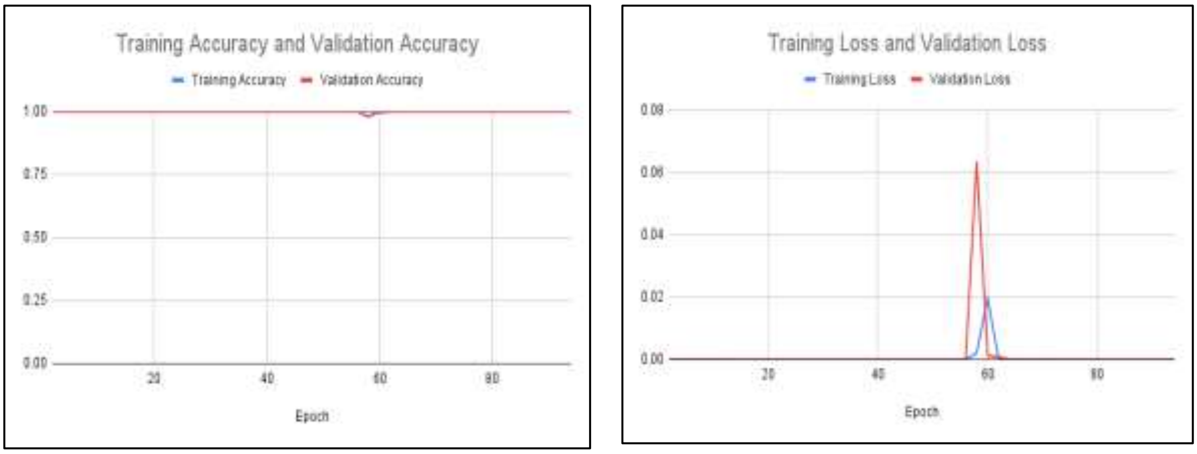

Figure 6: Training Accuracy vs Validation Accuracy and Training Loss vs Validation Loss

7. Conclusion

In conclusion, this paper demonstrates a pipeline for kidney image classification using a CNN model. It covers data loading, preprocessing, augmentation, model creation, training, evaluation, and model saving/loading. It also provides an example of how to use the trained model to make predictions on new images. The program utilizes libraries like OpenCV, NumPy, pandas, and TensorFlow to achieve its objectives.

References

Hoo-Chang Shin, Geoffrey E. Hinton, and Lee Fei-Fei, "Deep Learning for Medical Image Analysis", Journal of Medical Imaging, 2016

Geert Litjens, et al., "A Survey of Deep Learning in Medical Image Analysis", Medical Image Analysis, 2017

Lily Peng, et al., "Deep Learning-Based Automated Detection of Diabetic Retinopathy in Retinal Fundus Photographs", JAMA, 2018

S. H. Khan, et al., "Deep Learning for Medical Image Analysis: A Comparative Review", Journal of Medical Systems, 2019

Vishal M. Patel, et al., "Deep Learning for Medical Image Analysis: Introduction, Overview, and Challenges", IEEE Transactions on Medical Imaging, 2020

J. Deepa, et al., "A Review on Deep Learning Techniques for the Diagnosis of Kidney Diseases", Journal: Journal of King Saud University - Computer and Information Sciences, 2021

Le Lu, et al., "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?", IEEE Transactions on Medical Imaging, 2022. Bejan CA, Lee DJ, Xu Y, Hsi RS. Performance of a natural lan- guage processing method to extract stone composition from the electronic health record. Urology. 2019;132:56-62. https:// doi.org/10.1016/j.urology.2019.07.007.

Kazemi Y, Mirroshandel SA. A novel method for predicting kid- ney stone type using ensemble learning. Artif Intell Med. 2018; 84:117-126. https://doi.org/10.1016/j.artmed.2017.12.001.

Aldoukhi AH, Law H, Black KM, Roberts WW, Deng J, Ghani KR. PD04-06 deep learning computer vision algorithm for detecting kidney stone composition: towards an automated future. J Urol. 2019;201(4):e75-e76.

Kriegshauser JS, Silva AC, Paden RG, et al. Ex vivo renal stone characterization with single-source dual-energy computed to- mography: a multiparametric approach. Acad Radiol. 2016; 23(8):969-976. https://doi.org/10.1016/j.acra.2016.03.009.

Große Hokamp NG, Lennartz S, Salem J, et al. Dose indepen- dent characterization of renal stones by means of dual energy computed tomography and machine learning: an ex-vivo study. Eur Radiol. 2020;30(3):1397-1404. https://doi.org/10.1007/ s00330-019-06455-7.

Saçlı B, Aydınalp C, Cansız G, et al. Microwave dielectric prop- erty based classification of renal calculi: application of a kNN algorithm. Comput Biol Med. 2019;112:103366.

Cui X, et al. Preoperative prediction of infection stones using radiomics features from computed tomography. IEEE Access. 2019;7:122675-122683. https://doi.org/10.1109/ACCESS.2019. 2937907.