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Kidney Disease Classification Using Deep Learning Technique

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Abstract*— Kidney abnormality, which affects millions of individuals worldwide, is one of the key issues in modern society. Computed tomography, a narrow-beam x-ray imaging technology, is utilized to develop cross-sectional slices of the human kidneys to identify various disorders. Computer tomography images have been effectively classified and segmented using different deep-learning algorithms. However, it has proved challenging for healthcare professionals to comprehend the model's precise judgments, leading to a "black box" system. This study suggested a lightweight tailored convolution neural network to identify kidney cysts, stones, and tumours to get around these problems. The suggested CNN model outperformed other cutting-edge techniques and achieved an accuracy of 99.52. The suggested study gives practitioners definitive and clear data with improved outcomes and enhanced interpretative ability. Finally, the flask framework is used to predict web pages.

***Keywords*— kidney disease convolution neural network, flask framework, ct images.**

I. INTRODUCTION

Millions of individuals throughout the globe are affected by kidney disease, a serious health issue. Early and accurate diagnosis of kidney disease is critical for effective management and improved patient outcomes. Traditional diagnostic methods, such as imaging procedures, can be time-consuming and expensive. Recently, deep learning techniques have shown promise in improving the accuracy and efficiency of kidney disease diagnosis. These methods produce predictions based on learning from vast volumes of data using ANN (Artificial Neural Networks).

Deep learning models are effectively applied to various aspects of kidney disease diagnosis, including classification, segmentation, and progression prediction. In particular, deep learning models have shown promise in detecting various kidney issues, like tumors, cysts, and stones, from medical images. However, the interpretability of these models remains a challenge, as they can sometimes be seen as black boxes. Thus, there is a need to develop models that not only provide accurate predictions but also provide clinicians with understandable results.

II. LITERATURE REVIEW

A deep learning technique was utilised in research by Zou et al. to identify and categorise kidney tumours in CT images. The suggested technique extracted information from the input images using a CNN (Convolutional Neural Network) and a transfer learning approach. The extracted features were then used to classify kidney tumours into three categories: benign, malignant, or cysts. The potential of deep learning approaches in precisely identifying and categorising kidney tumours is shown by the suggested method's high accuracy of 94.4 percent in the categorization of kidney tumours. However, some limitations were identified in the study, including the relatively small size of the dataset used for training the model, which may affect the generalizability of the results. Furthermore, the interpretability of the model was not fully explored, and additional studies may be required to improve the model's interpretability.

To segment kidney lesions in CT images, Chen et al. developed a deep-learning technique. The suggested technique creates segmentation maps of kidney lesions by extracting features from the input CT images using a 3D convolutional neural network (CNN). The segmentation of kidney lesions using the suggested strategy produced a significant Dice coefficient of 0.83, demonstrating the potential of deep learning techniques in accurately segmenting kidney lesions.

Using ultrasound images, Yu et al. suggested a deep learning method for classifying the stages of chronic kidney disease (CKD). The suggested technique classified the CKD stages into five groups by extracting information from the input ultrasound images using a convolutional neural network (CNN): normal, mild, moderate, severe, and end-stage. The suggested technique classified the stages of CKD with 92.5 percent accuracy, demonstrating the potential of deep learning techniques in accurately classifying CKD stages using ultrasound images.

III. PROPOSED METHODOLOGY

The proposed methodology for kidney disease classification using deep learning techniques involves implementing a convolutional neural network (CNN) using Tensor Flow and Keras libraries in Python. The dataset used in this study is obtained from the CT-KIDNEY-DATASET, which contains four classes: normal, cyst, tumour, and stone.

Then the dataset is pre-processed using Image Data Generator, which rescales the pixel values to the range of [0, 1]. Six convolutional layers make up the CNN model, which is each followed by a max-pooling layer. The flattened output from the final pooling layer is passed through two fully connected layers, with the last layer having four nodes representing the four classes. The categorical cross-entropy loss function and RMSprop optimizer are used to develop a model.

The model is trained on the training set for five iterations, and after each iteration, it is verified on the validation set. The training process is monitored and visualized using various metrics, like loss, accuracy, recall, and precision. After training, the model is assessed on the test set using the evaluate method, which outputs different performance metrics, includingF1-score, accuracy, precision, and recall. A confusion matrix heatmap is also generated using the seaborn library to analyse the output of the model.

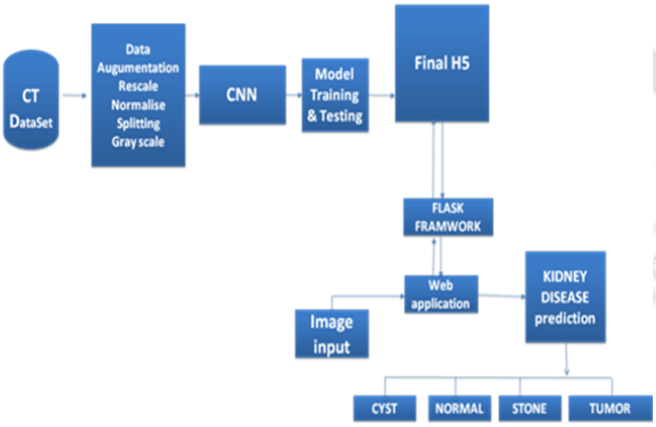

Figure 1. Proposed Architecture

Proposed modeules include:

- Data Collection
- Data Pre-processing
- Model Training
- Model Testing
- Flask Framework Prediction

A. Data Collection

The PACS: "Picture archiving and communication system" systems at different hospitals in Dhaka, Bangladesh, where patients had previously been recognised as having kidney stones, cysts, tumours, or normal results, were used to collect the dataset.

The Axial and Coronal slices were both taken from contrast and non-contrast tests with procedure for the whole urogram and abdomen.

Then, one diagnosis at a time, we formed a batch of Dicom pictures of the ROI for each radiological result from the carefully selected Dicom study.

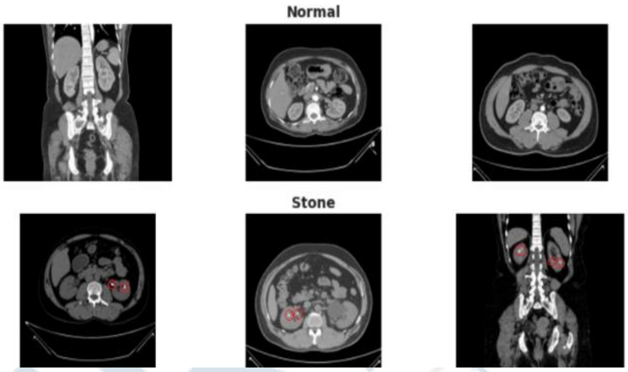

Figure 2. Data Sample

After removing the patient data and metadata, the Dicom images were then transformed to a lossless jpg image format. After conversion, every image result was double-checked by a radiologist and a medical technician to make sure the information was correct.

The aforementioned dataset comprises 12,446 different data points, 3,709 of which are cystic, 5,077 normal, 1,377 stone-related, and 2,283 tumour-related.

B. Preprocessing

Rescale parameter is set to 1/255, normalize to the range [0, 1]. target_size: A tuple specifying the size of the images after resizing. In this case, the images will be resized to 200x200 pixels. color_mode: Specifies whether the images should be loaded in colour ('rgb') or grayscale ('grayscale') mode. In this case, a grayscale mode is used. class_mode: Specifies the type of label encoding to use. 'categorical' is used here, which means that the labels are encoded as one-hot vectors. batch_size: Specifies the number of images in each batch. In this case, each batch will contain 100 images.

C. Model Training -CNN

Initializes a Sequential model and adds multiple layers to it using the Keras API with the TensorFlow backend.

The model architecture consists of 6convolutional layers with ReLU activation, followed by max-pooling layers to down sample the feature maps. The feature maps are flattened after the convolutional layers and then processed by a fully connected layer with 512 hidden units using ReLU activation. To finally categorize the input pictures into one of the four classes, the output layer is added. It has four neurons and a SoftMax activation function.

The optimizer used is 'rmsprop', and the loss function used is 'categorical_crossentropy', which is suitable for multi-class classification tasks.

Precision, recall, and accuracy are used as evaluation metrics for the model, and these metrics are defined in the METRICS variable.

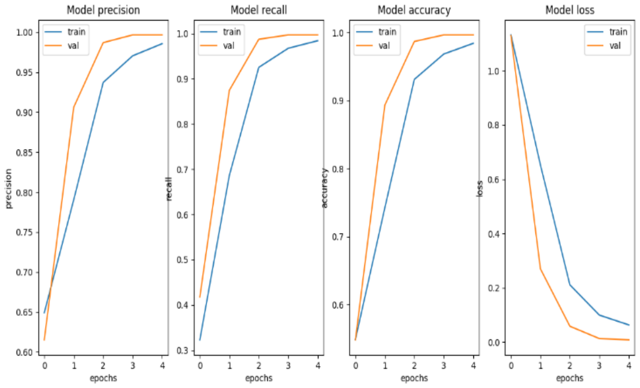

Figure 3. Training And Validation Graph

D. Model Testing

The word "data" is plural, not singular. Using the test dataset, we put the learned machine learning model to the test in this module.

- **Accuracy**

In reality, the most utilised statistic for model assessment is not a good indicator of performance. The worst happens when classes are not balanced.

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

- **Precision**

Percentage of positive occurrences from ***total predicted positive*** occurrences.

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

- **Logarithmic Loss:**

It is often called as log loss, works by penalizing false classifications. For multi-class classification, it works well. When applying Log Loss, the classifier should assign probabilities to each class for each sample. The log loss is calculated as follows, supposing there are N samples divided into M classes:

$$LogarithmicLoss = \frac{-1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij} * \log(p_{ij})$$

where p_ij is the probability that sample I matches to class j and y_ij denotes whether or not sample I matches to class j.

E. Flask Framework Prediction

A lightweight web framework for Python called Flask makes it simple and quick to develop web apps. Flask operates according to the MVC (Model-View-Controller) architectural pattern, in which the model represents the data, the view the user interface, and the controller serves as an intermediate between them.

Define routes: Routes are the URLs that the user can visit in your web application. You can define routes in Flask by using the @app.route() decorator and specifying the URL pattern as a parameter.

IV. RESULTS

The results observed from the deployment of our model developed is summarized through a confusion matrix and epoch graph table shown below:

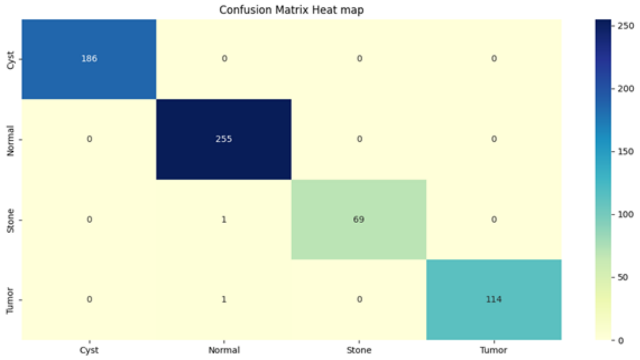

Figure 4. Confusion Matrix Heat Map

Epoch Number	Training				Validation			
	Accuracy	Precision	Recall	Loss	Accuracy	Precision	Recall	Loss
1	0.5489	0.6491	0.3229	1.1325	0.5484	0.6152	0.4177	1.1297
2	0.7427	0.7906	0.6857	0,6531	0.8935	0.9064	0.8742	0.2698
3	0.9313	0.9373	0.9250	0.2108	0.9871	0.9871	0.9871	0.0580
4	0.9687	0.9706	0.9672	0.0991	0.9968	0.9968	0.9968	0.0125
5	0.9844	0.9858	0.9839	0.0629	0.9968	0.9968	0.9968	0.0079

Figure 5. Epoch Graph Tabulation

V. CONCLUSION

Kidney abnormality is a major health concern globally, and the use of deep learning models in kidney disease diagnosis has shown promise in recent years. Specifically, in the detection of kidney cysts, stones, and tumours, a lightweight customized convolution neural network was proposed, which outperformed other novel approaches and achieved an accuracy of 99.52%. The proposed model also provides better interpretive power, enabling clinicians to understand the specific decisions made by the model. Additionally, the deployment of the model using the Flask framework for web page prediction makes it accessible to clinicians and patients, allowing for more efficient and accurate kidney disease diagnosis. Expanding the model's capabilities to identify other kidney problems should be the primary goal of future research in this field and validating the model's performance on larger datasets.

REFERENCES

[1] Maynar, J.; Barrasa, H.; Martin, A.; Usón, E.; Fonseca, F. Kidney Support in Sepsis. In *The Sepsis Codex-E-Book*; Elsevier Health Sciences: Amsterdam, The Netherlands, 2023; p. 169.

[2] Li, M.; Chi, X.; Wang, Y.; Setrerrahmane, S.; Xie, W.; Xu, H. Trends in insulin resistance: Insights into mechanisms and therapeutic strategy. *Signal Transduct. Target. Ther.* **2022**, *7*, 216.

[3] Yener, S.; Pehlivanoğlu, C.; Yıldız, Z.A.; Ilce, H.T.; Ilce, Z. Duplex Kidney Anomalies and Associated Pathologies in Children: A Single-Center Retrospective Review. *Cureus* **2022**, *14*, e25777.

[4] Sassanarakkit, S.; Hadpech, S.; Thongboonkerd, V. Theranostic roles of machine learning in the clinical management of kidney stone disease. *Comput. Struct. Biotechnol. J.* **2022**, *21*, 260–266.

[5] Kanti, S.Y.; Csóka, I.; Jójárt-Laczkovich, O.; Adalbert, L. Recent Advances in Antimicrobial Coatings and Material Modification Strategies for Preventing Urinary Catheter-Associated Complications. *Biomedicines* **2022**, *10*, 2580.

[6] Ramalingam, H.; Patel, V. Decorating Histones in Polycystic Kidney Disease. *J. Am. Soc. Nephrol.* **2022**, *33*, 1629–1630.

[7] Karimi, K.; Nikzad, M.; Kulivand, S.; Borzouei, S. Adrenal Mass in a 70-Year-Old Woman. *Case Rep. Endocrinol.* **2022**, *2022*, 2736199.

[8] Islam, M.N.; Hasan, M.; Hossain, M.; Alam, M.; Rabiul, G.; Uddin, M.Z.; Soylu, A. Vision transformer and explainable transfer learning models for auto-detection of kidney cyst, stone, and tumour from CT-radiography. *Sci. Rep.* **2022**, *12*, 11440.

[9] Qadir, A.M.; Abd, D.F. Kidney Diseases Classification using Hybrid Transfer-Learning DenseNet201-Based and Random Forest Classifier. *Kurd. J. Appl. Res.* **2023**, *7*, 131–144.

[10] Rajinikanth, V.; Durai Raj Vincent, P.M.; Srinivasan, K.; Ananth Prabhu, G.; Chang, C.Y. Framework to Distinguish Healthy/Cancer Renal CT Images using Fused Deep Features. Front. Public Health **2023**, 11, 39.