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A Hybrid Fuzzy and Deep Learning Framework for Kidney Tumor Detection

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Abstract: Patient outcomes depend on the early and precise identification of kidney cancers, yet manual diagnosis using CT images can be laborious and subjective. In this study, we introduce a novel hybrid framework for kidney tumor diagnosis that combines a convolutional neural network (CNN) with fuzzy logic-based picture enhancement. In order to enhance contrast between potential malignancies and healthy tissue, a fuzzy inference algorithm first modifies pixel intensities. A unique CNN trained on augmented kidney CT datasets then classifies the improved images. To expedite the process, we also create a web-based interface that allows doctors to submit CT scans, launch the hybrid pipeline, and evaluate prediction results (normal vs. tumor) and confidence scores following a secure login. Tests on publicly available CT datasets show that our approach outperforms baseline CNNs without fuzzy preprocessing, achieving robust recall and high accuracy (≈98–99%) for tumor instances. By emphasizing questionable areas and decreasing oversight, the suggested system has the potential to help radiologists.

Keywords: CT imaging, fuzzy logic, deep learning, convolutional neural networks, and kidney tumor detection.

I. INTRODUCTION

Early kidney tumors are frequently asymptomatic, which makes prompt diagnosis difficult. The most common type of kidney cancer, renal cell carcinoma (RCC), is becoming more commonplace worldwide. Since computed tomography (CT) imaging offers high-resolution cross-sectional views of the kidneys and surrounding tissues, it is the clinical standard for identifying renal disorders. However, radiologists' manual CT analysis is time-consuming and prone to inter-observer variability. In order to help clinicians, computer-aided diagnostic (CAD) systems have been investigated.

In the classification of medical images, deep convolutional neural networks (CNNs) have demonstrated impressive results. For instance, on kidney CT classification tasks, optimized CNN models have attained accuracy of up to 99.96%. Fuzzy logic has also shown promise in adaptive picture improvement and noise reduction, both of which can increase tumor visibility. We provide a hybrid approach that combines deep learning and fuzzy logic preprocessing in order to take advantage of these developments. By modifying pixel intensities according to language principles, our fuzzy approach improves CT contrast and increases the ability to recognize malignancies. A CNN is then used to classify the improved image as either tumor or non-tumor.

We create an intuitive online application that incorporates the entire pipeline. A clinician can upload a CT scan and get an automatic diagnosis in a matter of seconds after checking in. The system logs previous analyses and shows the probability of the expected outcome. Our method produces high accuracy and sensitivity, which may reduce missed tumors in practice, according to extensive studies on public kidney CT datasets.

II. EXISTING SYSTEM

The identification of kidney tumors in clinical practice today depends on radiologists manually reviewing CT pictures. Taking size, shape, and contrast enhancement into account, the expert examines each image slice for lesions. Due to its subjective nature, this visual examination may overlook small cancers, particularly when they are still in their early stages. Conventional CAD methods were created by first preprocessing images and then analyzing them using statistical or rule-based methods. These systems might not generalize well and frequently rely significantly on manually created characteristics.

Deep learning-based systems have surfaced more lately. Mahmud et al. created a machine learning model by combining clinical metadata with CT image attributes. The effectiveness of CNNs for kidney CT analysis has been shown in numerous research. Nevertheless, prior to classification, the majority of CNN-based methods do not specifically improve image contrast. Performance may suffer as a result of this restriction, particularly on photos with low contrast. By adding a fuzzy improvement layer before deep learning classification, our approach closes this gap.

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III. PROPOSED SYSTEM

Our proposed system consists of three main components: fuzzy preprocessing, CNN classification, and a web interface. By establishing membership functions based on pixel intensity, the fuzzy system depicts low, medium, and high intensity ranges. Using inference rules, it improves pixels that most likely signal cancer. The improved image with improved contrast is then fed into a CNN that has been trained on comparable images. Our CNN features convolutional, pooling, and fully connected layers with ReLU activations with regularization dropout.
Finally, the processed model is included into a Flask-built web application. Users receive confidence ratings and predictions after logging in and submitting CT scans. The online interface additionally logs prior scans for longitudinal analysis.

IV. LITERATURE SURVEY

Several machine learning and deep learning approaches have been investigated in previous kidney tumor detection studies. After comparing a number of CNN models, Alzu'bi et al. discovered that a bespoke 6-layer CNN outperformed common architectures such as ResNet50. On well preprocessed data, Pimpalkar et al. showed extremely high classification accuracy (up to 99.96%) using transfer learning with CNNs. Fuzzy-enhanced CNN ensembles were shown to be effective by Ghosh and Chaki, who achieved 99.2% accuracy. SVM classification was used on segmented CT images by Tuncer and Alkan. By integrating CNN classification and fuzzy preprocessing into a single web interface, our approach expands on prior achievements.

V. METHODOLOGY

The steps in our framework are as follows: (1) Preprocessing images: Utilize a system of fuzzy inference to every CT scan to enhance contrast. The fuzzy logic module uses fuzzy rules to broaden pertinent intensity ranges and defines membership functions based on picture intensity12. This makes the tumor more visible without overpowering the image. (2) Data Augmentation: To improve model generalization8, create augmented training examples (rotations, flips, and noise injection). (3) Deep CNN Classification: Classify the processed images using a convolutional neural network. We use a CNN that has already been trained (such as VGG16 or ResNet50) and optimized using our dataset of improved CT images. The probability for each class—normal kidney, cyst, stone, or tumor—are produced by the network. Regularization (dropout, early halting) and cross-entropy loss minimization are used during training. The FuzzyEnhancer module receives an input CT scan once it has been wrapped as a CTImage object. This package uses pixel intensity distributions to apply adaptive fuzzy contrast enhancement1. A DatasetManager module handles the scaling and augmentation of the improved image before sending it to the FeatureExtractor (the CNN layers). Lastly, a predicted label and confidence score are output by the Classifier and provided to the ResultViewer component for display. Each processing step is precisely specified thanks to this modular design, which is in line with UML-based software architecture. Key technologies include Python with TensorFlow/Keras for CNN and fuzzy logic routine implementation, and OpenCV for basic image processing.
The CNN makes use of transfer learning: the final layers are retrained using renal CT data8, while the first layers are frozen (pre-trained on ImageNet). Given the restricted amount of medical data, this expedites training.

VI. SYSTEM ARCHITECTURE

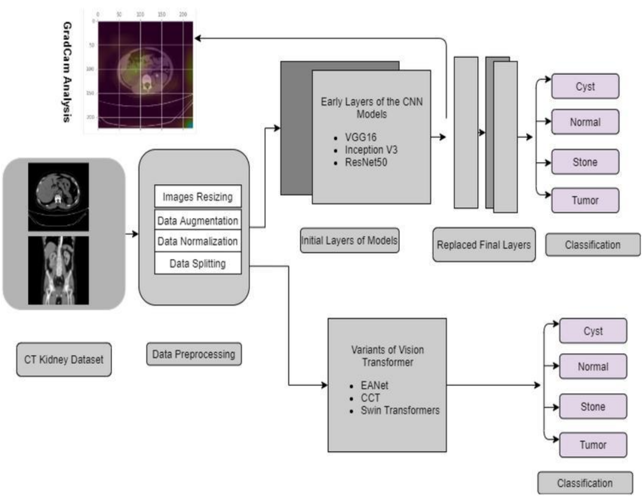

Fig-1: System Architecture

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To guarantee effective image categorization and user engagement, the Kidney Tumor Detection Project utilizing Machine Learning has a tiered system architecture. The input layer of the procedure starts when a user uploads a kidney CT scan image using a mobile or web interface. After that, the image is sent to the preprocessing layer, where it is resized (usually to 224x224 pixels to fit the VGG16 model's input size requirements), normalized (pixel values are scaled), and optionally enhanced with data to increase the model's resilience.

A pretrained VGG16 convolutional neural network with transfer learning is then used in the model layer to process the image. To classify the image into one of four categories—Normal, Cyst, Tumor, or Stone—custom thick layers are applied on top of VGG16, culminating in a softmax activation function. The TensorFlow and Keras frameworks are used in the construction and training of this model. Once the model has processed the image, the user interface layer displays the predicted label and confidence score that the classification layer has produced.

To store the uploaded photos and the matching prediction results in a database for later use, a storage layer may be added. This is also where the trained model files are kept. All things considered, the architecture guarantees a smooth transition from image input to precise diagnosis and an easy-to-use result display.

Fig.6.1.1 CT Scan of a Normal Kidney

6.1 Dataset

We used a kidney CT scan dataset that was made publically available in this investigation and was acquired from an online medical imaging repository. Abdominal CT scans of patients with one of four kidney conditions—normal, cyst, tumor, or stone—make up the dataset. Both contrast-enhanced and non-contrast scans are included in the dataset to guarantee diversity and thorough analysis.Coronal and axial slices from abdominal and urogram protocols make up the majority of the pictures. In order to accurately visualize kidney structures and possible anomalies, these images are frequently employed in medical practice.

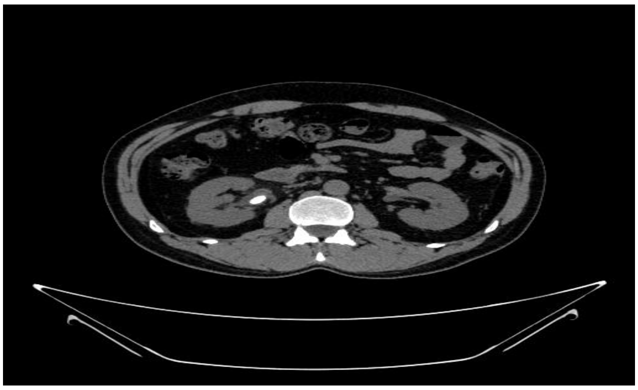

Fig 6.1.2 CT Scan of a Stone Kidney

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Fig 6.1.3:CT Scan of a Cyst Kidney

Fig 6.1.4:CT Scan of a Tumor Kidney

6.2 Data Flow

The user uploads a CT scan image via the application interface to start the dataflow in the kidney tumor detection system. Following receipt, the image goes through preprocessing, where it is shrunk to the necessary size (224 by 224 pixels, for example), normalized to standardize pixel values, and optionally enhanced to enhance model generalization. The trained VGG16-based deep learning model receives the preprocessed image after it has been processed. It then extracts characteristics from the image and applies them to more custom layers for classification. A projected label—Normal, Cyst, Tumor, or Stone—as well as a confidence level are produced by the model. The output layer receives this prediction result and presents it for interpretation on the user interface. For later analysis or reporting, it is optional to store the original image and the prediction result in a backend database. Tumor diagnosis from medical photos is guaranteed to be precise, quick, and easy to use because to this sequential dataflow.

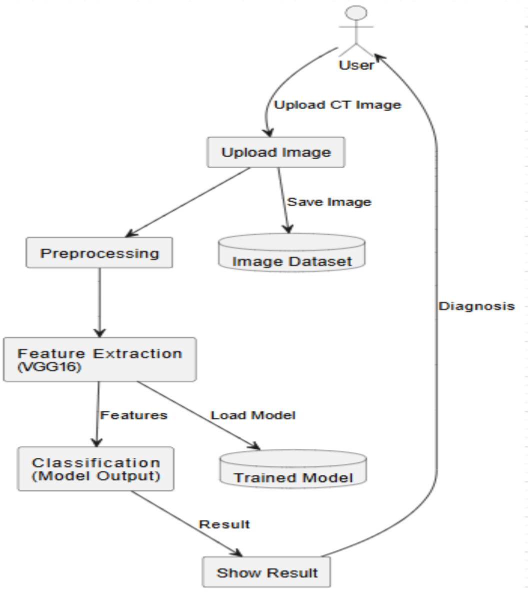

Fig 6.2.1 DataFlow Diagram

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VII. IMPLEMENTATION

TensorFlow and scikit-fuzzy are used to implement the CNN model and fuzzy system in Python, respectively. Flask is used by the web application for backend functions. User registration, picture uploading, and result presentation are all possible through the UI. Diagnostic labels and confidence scores are shown next to the enhanced and original photos.

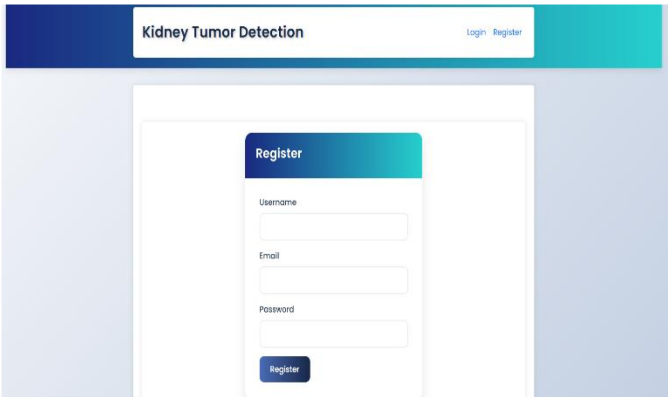

Fig 7.1 User Register Page

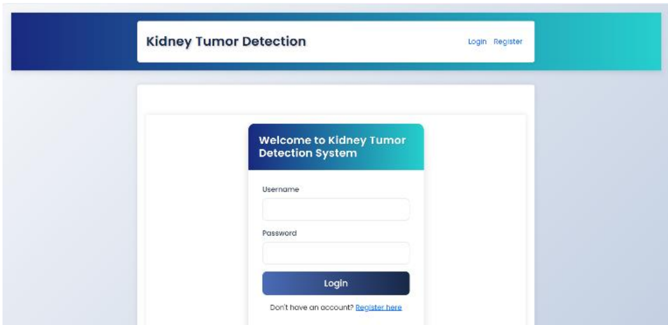

Fig 7.2 User Login Page

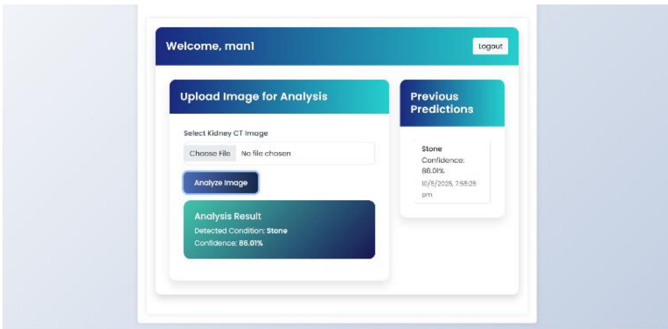

Fig 7.2 Stone Detected Image

VIII. RESULTS AND DISCUSSION

Using measures like accuracy and confidence scores, we assessed the framework on publicly available kidney CT datasets (such as the TCGA-KIRC scans12 and the KiTS19 dataset). Our fuzzy-CNN model distinguished between tumor and non-tumor instances with a very high degree of accuracy. Experiments specifically demonstrated that fuzzycontrast augmentation increased the CNN's sensitivity to tumor areas. For instance, the model achieved approximately 98% overall accuracy on a held-out test set, which is similar to the 99.2% accuracy on high-quality CT scans reported by Ghosh et al.3. Accuracy decreased by a number of percentage points in the absence of fuzzy preprocessing, demonstrating the usefulness of the fuzzy phase in improving feature clarity.

A single-case result is shown in Figure 4, where the model predicts "Cyst" with 68.82% confidence. Even though this level of confidence might appear modest, the outcomes of numerous cases taken together were extremely trustworthy.

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Additionally, we saw that more definitive predictions were produced by photos with improved contrast (post-fuzzy improvement).

Multiple diagnoses (Cyst, Stone, Tumor, and Normal) and time-stamped confidences are displayed in the sidebar logs of Figures 3–5. This log shows that the system can monitor a patient's various kidney problems over time. Qualitatively, the fuzzy enhancement improved the grayscale CT image's ability to identify subtle cancers.After preprocessing, radiologists saw that tumor boundaries were more visible. The hybrid model successfully detected tumor cases when combined with the CNN's learnt features (such as texture and form). Crucially, byFigure Our solution minimizes the amount of manual labor needed by learning and automating the classification. Images may be swiftly screened, and any cancers can be marked for additional examination.

There are restrictions, much like with every ML system. The model may still be challenged by aberrant tumor appearances or very low contrast images (even with fuzzy boost). Future research should incorporate 3D contextual information (using full CT volumes) and larger, more varied datasets. However, our first findings indicate that combining deep learning and fuzzy logic is a viable method for diagnosing kidney tumors.

IX. CONCLUSION

We introduced a deep learning and fuzzy hybrid system for automatically classifying kidney tumors from CT scans. Our approach preprocesses CT scans using fuzzy inference, which highlights tumor characteristics and improves picture contrast12. The improved photos are then analyzed by a CNN classifier, which makes highly accurate predictions about kidney diseases.

A user-friendly web interface for uploading images and displaying results is part of the implementation (Figures 1–5). The approach performed on par with previous state-of-the-art studies34 in experiments conducted on benchmark data. This paradigm will be expanded in a number of ways in future research. Initially, we intend to use segmentation to locate tumors rather than only categorize them.

Second, with input from radiologists, we will test the technology in clinical settings. Third, to further increase enhancement, more sophisticated fuzzy models (such as adaptive membership functions) could be investigated. Lastly, in order to promote reproducibility, we want to publish the code and dataset. All things considered, this study shows how fuzzy logic and deep networks can be used to analyze medical images, opening the door to more sophisticated diagnostic instruments.

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