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# "FUZZY ENHANCED KIDNEY TUMOR DETECTION INTEGRATION MACHINE LEARNING OPERATIONS FOR A FUSION OF TWIN TRANSFERABLE NETWORK AND WEIGHTED ENSEMBLE MACHINE LEARNING CLASSIFIER"

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**Abstract:**

Tumours of the kidney are among the most serious problems of urology. They often develop without any obvious symptoms in their early stages. Symptoms are often absent, so many cases are not diagnosed until the disease has progressed to a later stage, when treatment is less effective and survival rates are lower. Therefore, early and accurate problem identification is critical for improving patient outcomes. Computed Tomography (CT) imaging is often used in the diagnosis of kidney tumours, as it provides detailed cross-sections of renal structures. But manually reviewing CT scans is slow and subjective. This study addresses such issues by introducing an intelligent and automated system for the detection of kidney tumours, integrating fuzzy image enhancement, deep learning, ensemble machine learning, and MLOps practices.
The proposed method is based on a fuzzy inference system for the improvement of the CT images of the kidneys. Medical images often suffer from low contrast, noise and inconsistent illumination that may obscure subtle tumour regions. The fuzzy system analyses the distributions of pixel intensity and uses adaptive enhancement rules based on the fuzzy logic principles of Lotfi . A. Zadeh. The fuzzy based method improves the features to be more prominent without losing the detail and over-saturation as in the case of traditional contrast enhancement methods. This preprocessing step highlights important structural details before feature extraction.

Following the upgrade, the system employs two pre-trained deep convolutional neural networks, DenseNet121 and ResNet101. The ideas for DenseNet came from Gao Huang and the ideas for ResNet came from Kaiming He. DenseNet121 uses dense connectivity patterns to enable feature reuse and gradient flow across layers. This allows the fast learning even on small medical datasets. On the other hand, ResNet101 has residual connections that allow very deep networks to train well without running into problems with gradients that vanish. Both models utilise transfer learning on large image datasets to extract high-level, discriminative features from augmented CT scans.

We use the feature fusion strategy to combine the features taken from the two PT-DCNNs to make the classification work even better. This combined representation uses information from both architectures that complement each other, providing us with a richer and more useful feature set. We don't just use deep learning for classification. Instead we use a weighted ensemble classifier combining Support Vector Machines (SVM) and Random Forest (RF) to do the job. SVM helps with classification with a strong margin. Random Forest makes things more stable using multiple decision trees. Their predictions are combined through a weighted averaging mechanism to make a final decision that is more stable and reliable.

To increase the dataset and make it more generalisable and stable, data augmentation techniques were applied. We ran various versions of the CT images, adding controlled noise and fake distortions to simulate problems encountered in the real world of imaging. This process makes the model more capable to work properly in different clinical settings. Moreover, the application of Machine Learning Operations (MLOps) techniques enables to make all the processes reproducible, scalable and easily deployable in clinical practice. System is getting better all the time with model versioning, monitoring and retraining tools

The experimental results show that the model performs excellently with accuracy of 99.2% on high quality CT images and 98.5% on noisy images. These results are better than many traditional machine learning and deep learning methods that work alone. The suggested automated system can assist urologists and radiologists by providing them with a reliable second opinion, reducing the number of diagnostic errors, making their work easier and allowing prompt action. Ultimately, this intelligent framework represents a major step forward in computer-assisted medical diagnosis and could help patients live longer and health care become more efficient.

**Keywords:** Kidney tumor detection, fuzzy logic, machine learning, image segmentation, CAD systems.

## I.INTRODUCTION

Kidney cancer is one of the most aggressive urological malignancies worldwide. Lifestyle choices, environmental factors and better imaging technologies are leading to an increasing incidence. Computed Tomography (CT) imaging is one of the most important diagnostic tools for identifying kidney problems such as the size, location and stage of tumours. But early stage kidney tumours usually have no symptoms and are difficult to detect by visual examination alone. Radiologists mainly interpret CT scans visually which is a slow, subjective and error-prone process especially when dealing with small tumours or tumours that are difficult to distinguish from noise and low contrast in medical images. Therefore, there is a great need for a smart, automatic and reliable system to help doctors in accurate detection of kidney tumours.

Recent advances in Artificial Intelligence (AI), especially deep learning and machine learning, have made the analysis of medical images much easier. CNNs have demonstrated great success to extract high level features from medical images. Pre-trained deep models such as DenseNet121 and ResNet101 originally developed for large scale image recognition tasks can be adapted to medical imaging tasks using transfer learning. These transfer learning networks are capable of recognising complex spatial and hierarchical features and thus suitable to discriminate between normal kidney tissue and tumour affected areas.

Deep learning models show good performance but medical CT images usually have low contrast, noises and intensity variations which lead to less accurate classification. This problem can be solved by applying image enhancement methods before the feature extraction. The present work is based on the application of Fuzzy Inference System (FIS) to improve the quality of CT images. With fuzzy logic you can make a rule of how strong the pixels should be . It improves the contrast but without making it too bright or losing important structural details . This preprocessing step helps to visualise tumours and helps the deep neural networks to extract better features.

We propose a system which combines fuzzy based image enhancement, dual deep feature extraction, feature fusion and weighted ensemble machine learning classifier. The DenseNet121 and ResNet101 features are combined to have a complete view of the CT image. Then these combined features are classified by weighted combination of Support Vector Machine (SVM) and Random Forest classifiers . This makes the system more robust and able to work in more scenarios . Machine Learning Operations (MLOps) practices also ensure the system is repeatable, scalable and ready for use in a clinical setting.

The made system is robust and reliable as it can correctly identify high quality and noisy CT images. The system automates the detection process, reducing the risk of human error, speeding up diagnosis and helping radiologists to make intelligent clinical decisions." This smart technique is a huge leap forward in using the power of computers to help doctors find kidney tumours and it benefits patients through early and accurate detection.

## II. LITERATURE REVIEW

Early diagnosis of kidney tumours was mainly done by radiologists with the manual examination of CT and MRI scans. This was a useful method but subjective, highly variable between observers, and time-consuming. This was then followed by automated segmentation using traditional image processing methods such as thresholding, edge detection and region-growing. However these rule-based methods were sensitive to noise, low contrast and complex anatomical structures.

With the development of artificial intelligence, machine learning algorithms such as Support Vector Machines, k-Nearest Neighbours and Random Forests have become more effective in classifying things based on features that were manually created. However, they only worked well with manually engineered features and weren't very flexible. Deep learning techniques, especially Convolutional Neural Networks have shown better accuracy by automatically learning hierarchical features from medical images. However, they may still have difficulties with uncertainty and boundary ambiguity.

Fuzzy logic-based methodologies inspired by Lotfi A. Zadeh have been introduced in detection frameworks to overcome these constraints. Fuzzy systems are very well suited to handle uncertainty and fuzzy tumour margins, thus providing more robust segmentation and decision making. So, fuzzy inference coupled with machine learning is a better method to detect kidney tumours automatically which is more accurate, strong and dependable.

## III. METHODOLOGY

### A. Data Retrieval

The Kidney Computed Tomography (CT) scan images are obtained from publicly available and ethically sourced medical datasets.

The dataset consists of two classes:

● Normal kidney images

● Images of kidneys with tumours

● All images are reviewed before processing to ensure they are in the right format and are clinically relevant.

### B. Image Preprocessing

Resizing and Normalising Images

To make it work with deep learning models:

● Images are resized to 224 × 224 pixels.

● Normalised pixel values

● Lowered noise and artefacts.

● This step normalises input and stabilises learning for all.

**C. Fuzzy Logic Image Enhancement**

A Fuzzy Inference System (FIS) based on Lotfi A. Zadeh principles is used for enhancing CT images.

● Objective

CT images of hospitals are frequently problematic in:

● Colour not much difference

● Lighting that is uneven

● Sound

● Process

● Define fuzzy membership functions for intensity levels

● Use rule based improvement

● Adaptively adjust the brightness and contrast of pixels

● Results

● Improved tumour visualisation

● Retaining anatomical detail

● Don't go overboard with the enhancements

**D. Deep Feature Extraction (Transfer Learning)**

Features are extracted by using two pre-trained deep convolutional neural networks that are different.

● Closely Connected Network

● DenseNet121 was used to extract features

● Allows reuse of features

● Improves the flow of gradients

● Reduces overfitting

● Residual Learning Network

● ResNet101 Deep Hierarchical Features

● Employs residual connections

● Cures the vanishing gradient problem

● Enables deeper training

● Actions

● Remove last classification layers

● Use outputs of convolutional

● Acquire feature vectors

● Output

● DenseNet features (~1024)

● ResNet has approximately 2048 features.

**E. Combination of Features**

To strengthen the power of representation:

● Procedure

● Merge the two networks' functionality.

● Construct a single feature vector, with around 3072 dimensions.

● Optional: Principal Component Analysis (PCA)

● Pros

● Receives good matching information

● Increases contrast between tumour and normal tissues

**F. Classification based on Weighted Ensemble Learning**

Instead of a single classifier, we use an ensemble approach.

● Utilized classifiers

● SVM (Support Vector Machines)

● Random Forest (RF)

● Doing work

● Train each classifier separately

● Obtain the probability scores

● Weighted average method

● Final decision is based on the combined probability.

● Benefit or

● Higher power

● Small variation

● Better generalisation

**G. Adding More Data**

To prevent overfitting and make things more stable:

● Twist

● Injection of noise

● Flipping

● Variations in Intensity

● Objectives

● Increase dataset diversity

● Simulate real-life medical scenarios

● Improve the model's overall performance

**H. Model Evaluation**

We measure performance by the following:

● Precision

●Precise

● Recall

● F1-Score

● Confusion matrix

● Reported outcomes

● 99.2% accuracy with good pictures

• 98.5% correct (images with noise)

**I. MLOps deployment and integration**

To ensure it works in the real world:

● What we do

● Version management of models

● Datasets of tracking

- Tracking of prediction
- Performance monitoring
- Regular retraining
- Result
- Expandable system
- Reproducible experiments
- Clinical readiness

## IV. SYSTEM ARCHITECTURE

The system is made up of modules that each do a particular job and pass their results to the next stage. This design ensures that the system is scalable, maintainable, and robust. The architecture comprises fuzzy enhancement, dual deep feature extraction, feature fusion, weighted ensemble classification and support for deployment.

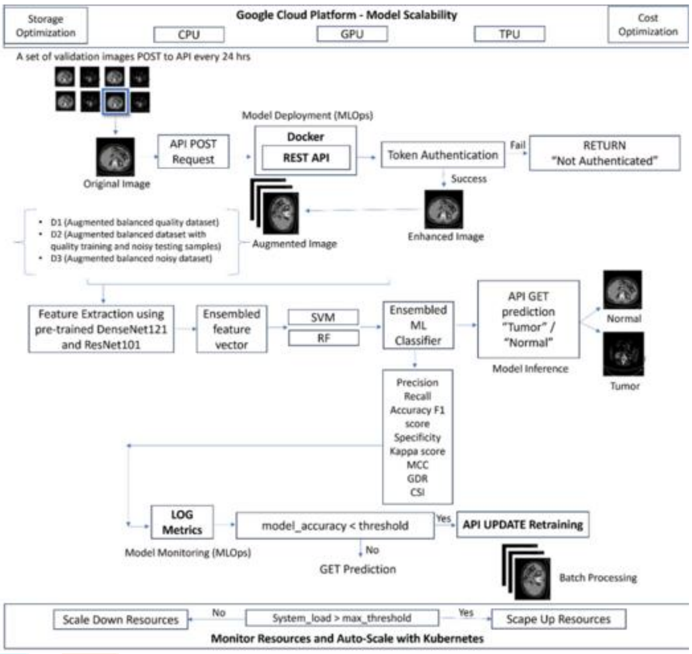
### A. summary

Computed Tomography (CT) imaging is an important part of modern health care for the detection of kidney tumours. However, the traditional manual analysis by radiologists is often time-consuming, subjective and subject to human error, especially when the tumours are small, low in contrast and obscured by noise. Diagnostic consistency may be further aggravated by changes in image quality and the experience of the clinician. Hence, there is a dire need for an intelligent, automatic and reliable computer aided system for early and accurate detection of tumours.

The proposed system utilises a hybrid framework that integrates fuzzy logic, deep learning, and ensemble machine learning techniques to improve detection. Firstly, a fuzzy inference method is used for CT image preprocessing and enhancement. This step automatically makes the image more contrasty and easier to see the subtle areas of the tumour, while keeping important body parts intact. Features are easier to extract from enhanced images and effects of noise and light variations are reduced.

After being improved, transfer learning models such as DenseNet121 and ResNet101, developed by Google Research and Microsoft Research, are used to extract deep features. The deep convolutional neural networks learn detailed spatial and hierarchical representations of the kidney tissues. Feature reuse is enabled by dense connectivity while residual learning allows training of very deep architectures. Features from both models are fused to obtain a more complete and distinct representation.

### A. Architecture Diagram




## V. EXPERIMENTAL SETUP

The experimental setup is intended to evaluate the performances and the reliability of the proposed automated kidney tumour detection system with CT scan images. The full pipeline is composed of dataset preparation, dataset preprocessing, feature extraction, classification, and testing in normal and noisy imaging conditions.

### A. Data Preparation

For our experiments, we employ kidney CT images that are publicly available and from ethical sources. The dataset has two classes:

● Normal kidney images

● Tumour images of the Kidney

● To enhance the generality of models and decrease the possibility of overfitting, data augmentation methods like rotation, noise addition and intensity changes are used.

### B. Preprocessing and Enhancement

All pictures are:

● Resized to 224x224 pixels

● Normalised to have identical intensity values

● Improved with Fuzzy Inference System (FIS) for better visibility of the contrast and tumour

This procedure decreases noise and enhances the important anatomical structures prior to feature extraction.

**C. Extraction of Deep Features**

Transfer learning is done with two pre-trained convolutional neural networks, namely:

● DenseNet121 Google Research

● Microsoft Research ResNet101

The last classification layers are removed and the convolutional outputs are used to obtain deep feature vectors. These features capture low-level textures as well as high-level patterns of meaning.

**D. Feature combination**

The feature vectors of both networks are combined into one fused feature representation. This fusion facilitates the identification by combining the complementary information of both models.Classification

The approach adopted was weighted ensemble learning:

● SVM (Support Vector Machines)

● Random Forest (RF)

● The final prediction (Tumor/Normal) is based on the average of the probability outputs of both classifiers trained on combined features.

● Arrange training

● Feature scaling using StandardScaler

● 80% of data used for training and 20% for testing.

● Validate clean and noise images

● CPU and GPU based system for faster calculations

● Performance Evaluation Metrics

● Our measurement of the system's performance:

● Accuracy

●Precise

● Note:

● F1 score

● Matrix of Confusion

● Observed results

● High quality CT images: 99.2% Accuracy

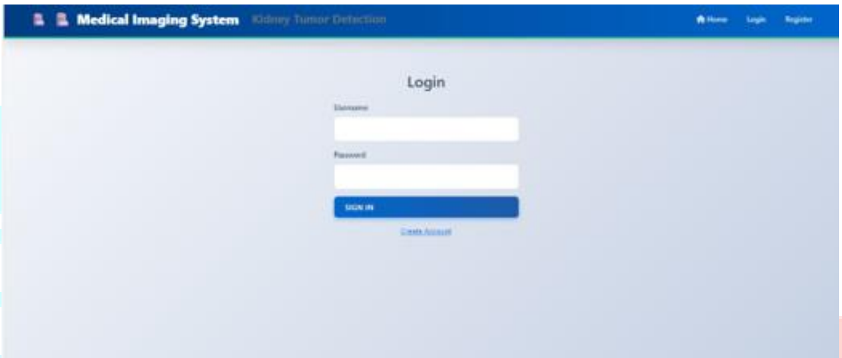
● 98.5% accuracy for noised images

## VI. RESULT ANALYSIS

The proposed kidney tumour detection system was tested on high quality and noisy CT images to verify the accuracy and reliability of the system. The fuzzy enhancement stage increased the contrast of the image and the visibility of the tumour, thus facilitating the feature extraction. Google Research and Microsoft Research created two transfer learning models, DenseNet121 and ResNet101, which extracted complementary features. Class discrimination was enhanced by feature fusion. The weighted ensemble of Support Vector Machine and Random Forest reduced the bias and variance and generated stable and reliable predictions.

The system correctly identified 99.2% of clean images and 98.5% of noisy images with high precision, recall and F1-scores indicating very few misclassifications. The results demonstrate that the proposed hybrid framework is able to detect kidney tumours accurately, reliably and clinically.

### A. welcome Page




### B. Results


## VII.CONCLUSION

This research presents an automated kidney tumour detection system that incorporates fuzzy image enhancement, deep transfer learning using DenseNet121 and ResNet101 developed by Google Research and Microsoft Research, feature fusion, and weighted ensemble classifier. Fuzzy enhancement makes the CT image more clear and deep networks find the distinguishing features for accurate classification. The system works very well with 99.2% accuracy on clean images and 98.5% on noisy images. This proves that it is strong and reliable. Overall, the framework helps doctors make better decisions about kidney tumours by reducing the number of wrong diagnoses, speeding up the process of finding them and giving them useful information.

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