Kidney Neoplasm Identification Using Fuzzy-Augmented Learning with Transferable Dual-Network Fusion and Weighted Ensemble Classification

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Abstract:

Kidney tumours are one of the most serious urological problems. They often grow without any noticeable symptoms in their early stages. Because they often don't show any symptoms, many cases go undetected until the disease has progressed to a more advanced stage, which makes treatment less effective and lowers survival rates. So, finding problems early and correctly is very important for improving patient outcomes. Computed Tomography (CT) imaging is commonly employed for kidney tumour diagnosis because it offers comprehensive cross-sectional representations of renal structures. But looking at CT scans by hand can take a long time and be different for each person. This study tackles these issues by suggesting an intelligent and automated system for finding kidney tumours that uses fuzzy image enhancement, deep learning, ensemble machine learning, and MLOps practices.

The proposed method starts with a fuzzy inference system that is meant to improve CT images of the kidneys. Medical images frequently exhibit low contrast, noise, and inconsistent illumination, which may obscure subtle tumour regions. The fuzzy system looks at the distributions of pixel intensities and uses adaptive enhancement rules based on Lotfi A. Zadeh's fuzzy logic principles. The fuzzy-based method makes features more visible without losing detail or causing over-saturation, which is what happens with traditional contrast enhancement methods. This step of preprocessing makes sure that important structural details stand out before feature extraction.

After the upgrade, the system uses two pre-trained deep convolutional neural networks: DenseNet121 and ResNet101. Gao Huang came up with the ideas for DenseNet, and Kaiming He came up with the ideas for ResNet. DenseNet121 uses dense connectivity patterns to make feature reuse easier and gradient flow better across layers. This lets it learn quickly even with small medical datasets. ResNet101, on the other hand, has residual connections that let very deep networks train well without running into problems with gradients that disappear. Both models use transfer learning from large image datasets to get high-level and discriminative features from enhanced CT images.

We use a feature fusion strategy to combine the features taken from the two PT-DCNNs to make classification work even better. This ensemble representation takes information from both architectures that work well together, which gives us a feature set that is richer and more useful. We don't just use deep learning for classification. Instead, we use a weighted ensemble classifier that combines Support Vector Machines (SVM) and Random Forest (RF) to do the job. SVM helps with strong margin-based classification, and Random Forest makes things more stable by using multiple decision trees. A weighted averaging mechanism combines their predictions to make a final decision that is more stable and reliable.

Using data augmentation methods, the dataset was made bigger to make it more generalisable and stable. We made different versions of CT images by adding controlled noise and fake distortions to make them look like real-world imaging problems. This process makes the model better able to work correctly in a variety of clinical situations. Also, using Machine Learning Operations (MLOps) practices makes sure that everything can be repeated, scaled up, and deployed smoothly in clinical settings. Model versioning, monitoring, and retraining tools help the system get better all the time.

The experimental results show that the model works very well, with 99.2% accuracy on high-quality CT images and 98.5% accuracy on noisy images. These results are better than those of many traditional machine learning and deep learning methods that work on their own. The proposed automated system can help urologists and radiologists by giving them a reliable second opinion, lowering the number of diagnostic mistakes, making their jobs easier, and making it easier to act quickly. In the end, this smart framework is a big step forward for computer-aided medical diagnosis and could help patients live longer and make healthcare more efficient.

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

I.INTRODUCTION

Kidney cancer is one of the most serious urological cancers in the world. Its incidence is rising because of lifestyle choices, environmental factors, and better imaging technologies. Computed Tomography (CT) imaging is one of the most important diagnostic tools for finding kidney problems, such as tumours' size, location, and stage. But kidney tumours in their early stages often don't show any signs and can be hard to find just by looking at them. Radiologists depend a lot on how they see CT scans, which can take a long time, be subjective, and be wrong because of human error, especially when tumours are small or hidden by noise and low contrast in medical images. So, there is a huge need for a smart, automated, and dependable system that helps doctors find kidney tumours accurately.

Recent developments in Artificial Intelligence (AI), especially deep learning and machine learning, have made it much easier to analyse medical images. Convolutional Neural Networks (CNNs) have shown great success in getting high-level features from medical images. Transfer learning can be used to adapt pre-trained deep models like DenseNet121 and ResNet101, which were originally made for large-scale image recognition tasks, to medical imaging tasks. These transferable networks can pick up on complicated spatial and hierarchical features, which makes them good for telling the difference between normal kidney tissues and areas affected by tumours.

Deep learning models work well, but medical CT images often have low contrast, noise, and changes in intensity that can make classification less accurate. To get around this problem, image enhancement methods must be used before feature extraction. This project uses a Fuzzy Inference System (FIS) to improve the quality of CT images. Fuzzy logic lets you change the intensity of pixels based on rules, which improves contrast without making things too bright or losing important structural details. This preprocessing step makes tumours easier to see and makes the features that deep neural networks extract better.

The suggested system combines fuzzy-based image enhancement, dual deep feature extraction, feature fusion, and a weighted ensemble machine learning classifier. DenseNet121 and ResNet101 features are combined to make a full picture of the CT image. Then, a weighted combination of Support Vector Machine (SVM) and Random Forest classifiers is used to classify these combined features. This makes the system more robust and able to work in more situations. Also, using Machine Learning Operations (MLOps) practices makes sure that the system can be repeated, scaled up, and ready for clinical use.

The system that was made can accurately detect both high-quality and noisy CT images, showing that it is strong and dependable. The system automates the detection process, which reduces the chance of human error, speeds up diagnosis, and helps radiologists make smart clinical decisions. This smart method is a big step forward in using computers to help doctors find kidney tumours, and it helps patients by finding them early and accurately.

II. LITERATURE REVIEW

Radiologists mostly used manual examination of CT and MRI scans to find kidney tumours early. This method worked, but it took a long time, was subjective, and had a lot of variability between observers. Later, automated segmentation used traditional image processing methods like thresholding, edge detection, and region-growing. However, these rule-based methods had trouble with noise, low contrast, and complicated anatomical structures.

As artificial intelligence has gotten better, machine learning algorithms like Support Vector Machines, k-Nearest Neighbours, and Random Forests have gotten better at classifying things by using features that were made by hand. But they only worked well when features were manually engineered, and they weren't very flexible. Deep learning methods, especially Convolutional Neural Networks, have shown better accuracy by automatically learning hierarchical features from medical images. However, they may still have problems with uncertainty and boundary ambiguity.

To overcome these constraints, fuzzy logic-based methodologies, influenced by Lotfi A. Zadeh, have been incorporated into detection frameworks. Fuzzy systems work well with uncertainty and unclear tumour boundaries, which makes segmentation and decision-making more reliable. So, using fuzzy inference and machine learning together is a better way to automatically find kidney tumours that are more accurate, strong, and dependable.

III. METHODOLOGY

A. Getting Data

We get Kidney Computed Tomography (CT) scan images from publicly available and ethically sourced medical datasets.
There are two classes in the dataset:

- Images of normal kidneys
- Images of kidneys with tumours
- Before processing, all images are checked to make sure they are in the right format and are clinically relevant.

B. Preprocessing of Images

Resizing and Normalising Images

To make sure it works with deep learning models:

- The size of the images is changed to 224 × 224 pixels.
- Normalised pixel values
- There is less noise and artefacts.
- This step makes input the same for everyone and makes learning more stable.

C. Image Enhancement Using Fuzzy Logic

A Fuzzy Inference System (FIS) grounded in the principles of Lotfi A. Zadeh is utilised to improve CT images.

- Goal

CT images from hospitals often have problems with:

- Not much difference in colour
- Lighting that isn't even
- Sound
- Procedure

- Set up fuzzy membership functions for levels of intensity
- Use rule-based improvement
- Change the brightness and contrast of pixels in an adaptive way
- Result
- Better view of the tumour
- Keeping anatomical details intact
- Not going overboard with enhancements

D. Deep Feature Extraction (Learning to Transfer)

Two deep convolutional neural networks that have already been trained are used to find features that are different.

- Network of Dense Connections
- DenseNet121 used to get features
- Promotes the reuse of features
- Makes the flow of gradients better
- Lessens overfitting
- Residual Learning Network
- ResNet101 for deep hierarchical features
- Utilises residual connections
- Stops the problem of the vanishing gradient
- Allows for more in-depth training
- Steps
- Take off the last layers of classification
- Utilise convolutional outputs
- Get feature vectors
- Output
- DenseNet features (~1024)

- ResNet has about 2048 features.

E. Combining Features

To make the power of representation stronger:

- **Method**
- **Put together features from both networks.**
- **Make a single feature vector with about 3072 dimensions.**
- **Optional dimensionality reduction (PCA)**
- **Advantage**
- **Gets information that goes well with it**
- **Improves the distinction between tumour and normal tissues**

F. Using Weighted Ensemble Learning to Classify

An ensemble approach is used instead of just one classifier.

- Used Classifiers
- Machine for Support Vectors (SVM)
- Random Forest (RF)
- Doing work
- Train each classifier separately
- Get probability scores
- Use weighted averaging
- The final decision is based on the combined probability.
- Benefit
- More strength
- Less variation
- Improved generalisation

G. Adding More Data

To stop overfitting and make things more stable:

- **Turn**
- **Adding noise**
- **Flipping**
- **Changes in intensity**
- **Goal**
- **Make the dataset more diverse**
- **Simulate real-life medical situations**
- **Make the model work better in general**

H. Evaluation of the Model

We use the following to measure performance:

- Correctness
- Exactness
- Remember
- F1-Score
- Matrix of Confusion
- Results that were reported
- 99.2% accuracy with clear pictures
- 98.5% correct (images with noise)

I. Putting it into use and integrating MLOps

To make sure it works in the real world:

- Things we do
- Version control for models
- Keeping track of datasets
- Keeping track of predictions
- Keeping an eye on performance

- Ongoing retraining
- Result
- System that can grow
- Experiments that can be repeated
- Readiness for clinical deployment

IV. SYSTEM ARCHITECTURE

The system is made up of modules that each do a specific job and send their results to the next stage. This design makes sure that the system can grow, is easy to maintain, and works well. The architecture includes fuzzy enhancement, dual deep feature extraction, feature fusion, weighted ensemble classification, and support for deployment.

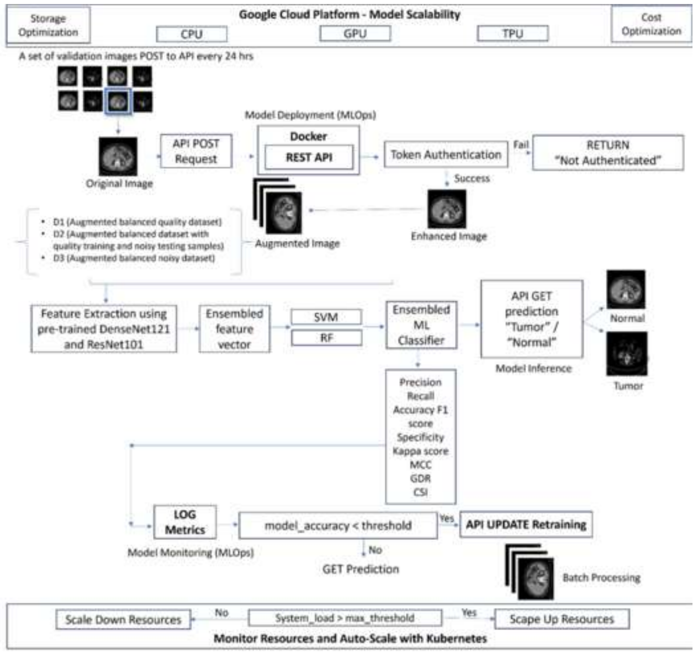
A. overview

Using Computed Tomography (CT) imaging to find kidney tumours is an important part of modern healthcare. Radiologists' traditional manual analysis, on the other hand, is often slow, subjective, and prone to human error, especially when tumours are small, have low contrast, or are hidden by noise. Changes in the quality of images and the experience of the clinician may make diagnostic consistency even worse. So, we need a smart, automated, and dependable computer-aided system to help find tumours early and accurately.

The proposed system uses a hybrid framework that combines fuzzy logic, deep learning, and ensemble machine learning methods to make detection better. At first, a fuzzy inference mechanism is used to preprocess and improve CT images. This step automatically makes the image more contrasty and easier to see subtle tumour areas while keeping important body parts intact. Enhanced images make it easier to extract features and lessen the effects of noise and changes in light.

After enhancement, transfer learning models like DenseNet121 and ResNet101, which were made by Google Research and Microsoft Research, are used to extract deep features. These deep convolutional neural networks make detailed spatial and hierarchical representations of kidney tissues. Dense connectivity makes it easier to reuse features, and residual learning makes it possible to train very deep architectures. The features from both models are combined to make a more complete and distinct representation.

B. Architecture Diagram



V. EXPERIMENTAL SETUP

The experimental setup is meant to test how well and how reliably the proposed automated kidney tumour detection system works with CT scan images. The whole pipeline includes preparing the dataset, preprocessing it, extracting features, classifying it, and testing how well it works in both normal and noisy imaging conditions.

A. Getting the Dataset Ready

We use kidney CT images that are publicly available and come from ethical sources for our experiments. There are two classes in the dataset:

- Images of normal kidneys
- Images of kidneys with tumours
- Data augmentation techniques like rotation, noise addition, and intensity variations are used to make models more general and less likely to overfit.

B. Preprocessing and Improvement

All pictures are:

- Changed to 224 × 224 pixels
- Normalised to have the same intensity values
- Improved with a Fuzzy Inference System (FIS) to make the contrast and tumour more visible

This step cuts down on noise and brings out important anatomical structures before feature extraction.

C. Extracting Deep Features

Two pre-trained convolutional neural networks are used for transfer learning:

- Google Research DenseNet121
- Microsoft Research ResNet101

The last classification layers are taken away, and convolutional outputs are used to get deep feature vectors. These features pick up both low-level textures and high-level patterns in meaning.

D. Merging Features

The feature vectors from both networks are combined to make one fused feature representation. By combining complementary information from both models, this fusion makes it easier to tell the difference.Categorisation

A weighted ensemble learning approach is employed:

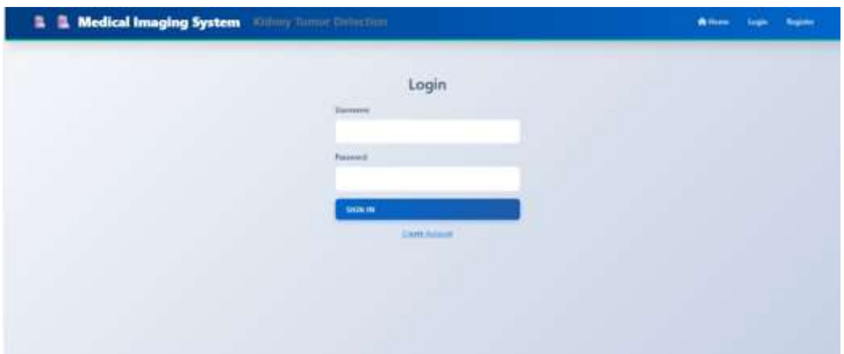
- Support Vector Machine (SVM)
- RF (Random Forest)
- Both classifiers are trained on combined features, and the final prediction (Tumor/Normal) is based on the average of their probability outputs.
- Setting up the training
- StandardScaler for feature scaling
- 80% of the data is used for training and 20% for testing.
- Check both clean and noisy images
- System with CPU and GPU for faster calculations
- Metrics for Evaluating Performance
- We measure how well the system works by:
- Correctness
- Exactness
- Remember
- F1-score
- Matrix of Confusion
- Results that were seen
- 99.2% accuracy on CT images of high quality
- 98.5% correct on pictures with noise

VI. RESULT ANALYSIS

We tested the proposed kidney tumour detection system on both high-quality and noisy CT images to see how accurate and reliable it was. The fuzzy enhancement stage made the image's contrast and tumour visibility better, which made it easier to extract features. Google Research and Microsoft Research made two transfer learning models, DenseNet121 and ResNet101, that pulled out complementary features. Feature fusion improved class discrimination. By lowering bias and variance, the weighted ensemble of Support Vector Machine and Random Forest made predictions that were stable and dependable.

The system got 99.2% of clean images right and 98.5% of noisy images right, with high precision, recall, and F1-scores, which means there were very few misclassifications. These results show that the suggested hybrid framework can accurately, reliably, and clinically detect kidney tumours.

A. welcome Page



B. Results

VII.CONCLUSION

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

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