Research Article

Artificial Intelligence in Renal Oncology: CNN-Based Classification of Kidney Cancer

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Abstract: Medical researchers worldwide identify kidney cancer as a major mortal and morbid disease while its early-stage detection significantly improves patient survival potential. Global diagnostic practices based on imaging and biopsy techniques carry both costly intrusiveness and potential human errors in their diagnostic results. This research creates an automatic kidney cancer diagnostic system which utilizes deep learning CNN models and applies ResNet transfer learning techniques. Through the use of pre-trained ResNet architectures the model demonstrates robustness for classifying benign versus malignant kidney tumor images found in CT scans. The training process utilizes a kidney CT image dataset that required various preprocessing steps for both data augmentation and normalization and size adjustment to create a generalized model. The deep learning framework showcases superior performance than standard approaches while delivering a 92% accuracy rate through productive F1-scores alongside precise recall metrics. The Area Under the Curve metric of 0.95 demonstrates the model's powerful discriminatory performance. The utilization of ResNet transfer learning enabled models to extract meaningful insights from restricted datasets thereby minimizing dependence on lengthy labeled datasets while preserving prediction accuracy. The study demonstrates how CNN-based techniques present a promising diagnostic framework for clinical kidney cancer detection which combines accuracy with efficiency and non-invasiveness for aiding radiologists and clinicians during diagnostics.

Keywords: Kidney Cancer, Deep Learning, Convolutional Neural Networks (CNN), ResNet, Transfer Learning, Medical Imaging, Classification, Tumor Diagnosis, CT Scans, Automated Diagnosis, Precision Medicine, Image Augmentation, AUC, Binary Classification, Radiology

1. Introduction

The worldwide occurrence of kidney cancer represents one of the leading causes of cancer deaths while showing rising diagnostic frequency. The current diagnostic tools built around CT scans and biopsy testing demand human operators to interpret results but both struggle with precision and delay medical assessments. Through an analysis of deep learning methods and Convolutional Neural Networks (CNNs) we examine their potential to automate kidney cancer diagnosis from medical images with the goal of improving medical precision and decreasing human intervention.

Image classification benefits greatly from Convolutional Neural Networks (CNNs) because these networks learn hierarchical features automatically from image data [2][3]. Various cancer detection applications in medical imaging take advantage of these networks which have widespread use for skin cancer detection and breast cancer diagnosis and brain tumor classification [1][[20][23]. The implementation of CNNs in medical image analysis meets difficulties due to restricted access to substantial labeled datasets needed to train deep learning models effectively.

The problem requires a solution from transfer learning which utilizes pre-trained models on large-scale datasets that include ImageNet [4][5]. Transfer learning applications prefer ResNet as their leading model because its deep architecture training capacity enables high performance across various image recognition tasks [6][7]. The method enables networks to extract image knowledge from extensive datasets before adapting this expertise to medical diagnostic tasks including kidney cancer detection.

This research work introduces a ResNet-based CNN framework for the automatic classification process of kidney tumor images into benign and malignant zones. We use CT scan data through transfer learning with ResNet50 which is a ResNet variant as our diagnostic framework. The main goal of this research establishes a sophisticated deep learning solution which effectively and rapidly determines the nature of kidney tumors for better diagnostic accuracy.

This research hypothesizes that applying ResNet transfer learning enhances diagnostic accuracy when analyzing small medical datasets. This paper follows the following structure: The paper structure includes Section 2 for discussing related works and medical imaging applications of deep learning while Section 3 describes the methodology with relevant dataset information then provides results in Section 4 and concludes in Section 5.

2.Literature Review

Medical image classification by deep learning methods (DL), in recent years has made tremendous progress with regards to cancer diagnosis. Convolutional Neural Networks (CNN) currently is the universal deep learning architecture in the lab, because they automatically extract detailed features in medical imaging data. The article evaluates kidney cancer diagnosis systems powered by ResNet and other CNN-based architectures through various studies to determine their benefits and shortcomings and analyze the effect of transfer learning on these systems.

2.1 CNN in Medical Image Analysis

The deep learning revolution in image processing was ignited by CNNs in the very influential work of the authors Krizhevsky et al. (2012) for medical image related. Experiments proved CNN to outperform conventional learning algorithms hence making them very much useful in clinical scenario in the video such as radiology and dermatology [8]. By definition these models obtain image features in hierarchical ways without the need of any human intervention on constructing features. Moreover, the research of Han et al. (2018) has been successful with renal tumor segmentation on CT images in CNN models based [9]. This report validates the ability of deep learning to find kidney tumor that CNN models surpass the thresholding and region growing approaches both in speed and accuracy.

2.2 Multi-phase CT Imaging for Tumor classification

Park et al. (2020) developed an automatic diagnosis system for kidney masses using multi-phase CT scans as a study. Since the model constructed in this thesis was shown to have superior classification performance in relation to a deep learning framework, it can detect important renal mass characteristics throughout the different stages of contrast enhancement which are essential for the accurate diagnosis [10].

2.3 Transfer Learning in Medical Imaging

This practice of using transfer learning methods has become common in medical imaging applications since access to sufficient labeled medical data is not easy. (TAG-2016) measured the adaptability of transfer learning to CNNs studying complete training methodology as well as pre-trained model fine-tuning practice. The researchers showed that pre-trained model optimization would minimize reliance on huge datasets without affecting performance levels [11].

2.4 ResNet for Medical Image Analysis

Medical imaging researchers borrowed ResNet (Residual Networks) from He et al. (2016) since it solves the vanishing gradient problem, and it has a deep architecture structure [12]. Result from machine learning models with ResNet50 model shows that deep features extracted from CT scans and MRI images are capable of detecting kidney cancer with a notable increment in detection accuracy.

2.5 Multi class Kidney Tumor Classification

Mahmood et al. (2021) operated a multi-class deep learning classifier that differentiates kidney CT images into normal tissue cysts stones and tumors [21]. The proposed system combined deep neural and classic radiomic features to demonstrate how such combinations result in better classification procedures. Similarly, Abdullah et al. (2024) provided comprehensive elucidation of predictive methods on chronic kidney disease [13].

2.6 Hybrid Models for Kidney Cancer Classification

Ensemble deep learning models combining approaches for classification of kidney cancer were studied by Yu et al. (2019) and Hussain et al. (2021). Contributions to the improvement of classification results were made through the combination of several models blending CNNs with support vector machines (SVM) for problematic datasets [14][15].

2.7 U-Net for Kidney Tumor Classification

For the segmentation of kidney tumor's, a U-Net-based architecture developed by Xu et al (2021) for kidney cancer diagnosis is needed. To enhance the accuracy in segmentation when looking at CT images, the model adopted encoder-decoder structures as per the study [16].

2.8 Ealuation metrices for Kidney cancer classification

EvShin et al. (2016) and other research teams used the model performance evaluation by means of the AUC (Area Under the Curve) and F1-score assessment methods. These metrics are the standard criterion for classifying medical models' analysis because in medical applications, there is both required sensitivity in addition to specific specificity [23].

2.9 Explaining Deep Learning Models in Medical Applications

The deep learning model explainability is still a critical topic in healthcare. The work by Cheng et al. (2015) and Esteva et al. (2017) was done to make use of deep learning models more transparent for tumor classification. This study calls for making the models interpretable specifically for radiologists to accept and utilize these AI solutions [18] [19].

Kidney cancer, as one of the most common cancers of the world and poses one challenging problem of diagnosis in terms of the complexity of its imaging signs and the fine line between benign and malignant tumors. Traditional diagnostic methods include imaging technologies, such as Computed Tomography (CT) scans and Magnetic Resonance Imaging (MRI), and biopsy, which are often invasive, laborious, and operative on the judgment of radiologists leading to diagnostic inaccuracies and delays. Although medical image technology has improved immensely, the interpretation of medical images is still done by a human factor, the demand for quicker, more precise and more automated diagnostic tools is essential for improving the patient outcomes.

Recently, deep learning methods, particularly Convolutional Neural Networks (CNNs), have demonstrated favorable performances in computer assisted analysis of medical images [22]. Yet, the difficulty lies in how to actually use CNNs in kidney cancer detection from CT images as small and unbalanced medical image datasets incur mongering accurate and dependable outcomes. Also, training deep learning models from scratch is computationally expensive requiring large labeled datasets which are often missing in the medical research [17].

3. Dataset and Preprocessing

3.1 Dataset and Description

The dataset used here consists of CT images of kidney tumors annotated as benign or malignant. The data is obtained by using publicly available medical imaging repository by using Kaggle and an academic repository curated specifically towards medical image analysis. These images are usually filed in DICOM format, in little the standard storage of medical imagery date.

Number of Images: The dataset contains a total of 3,000 CT images of kidney tumors.

- Benign Tumors: 2,000 images
- Malignant Tumors: 1,000 images

The images are evenly distributed between the two classes, ensuring a balanced classification task.

- Image Dimensions: The original CT scan images are of varying sizes. These are resized to a 224x224 pixels resolution to meet the input requirements of the ResNet50 model.
- Labeling: Each image is labeled as either benign (non-cancerous) or malignant (cancerous), based on expert annotations.

The dataset is divided into three subsets for model training, validation, and testing to ensure a robust evaluation:

- Training Set: 80% (2,400 images)
- Validation Set: 10% (300 images)
- Test Set: 10% (300 images)

Each subset contains a balanced distribution of both benign and malignant images, ensuring unbiased training and evaluation.

3.2 Dataset Preprocessing Pipeline

The preprocessing pipeline turbocharges the dataset for the deep learning model training, by standardizing all images to the final form to achieve the best performance on the model. The following preprocessing have been applied:

1. Resizing: All images are resized to 224x224 pixels for consistency with ResNet50 architecture's input size. The standardization guarantees that the uniformity of the dataset.
2. Normalization: To Normalize the pixel value with the range of [0, 1] each pixel value is divided by 255. This normalizes your data bringing pixel values within a specific range - which is useful for the deep learning model to make the training process faster.
3. Data Splitting: This dataset is split into three sets (training, validation, test) in order to ensure that the model trains on images, validates on images and test on images in order to avoid over training. The partition also ensures that the Partition also guarantees that the appropriate images are evenly distributed in the individual sets benign and malignant.
4. Color Channel Conversion: As images are RGB (three channels) the pca () pipeline ensures they're uniform across all samples. This step leads to compatibility with the form of input of the model.

3.3 Dataset Augmentation

For the model to be more able to generalize, augmented data is used during training. Data augmentation artificially increases the size of the original training dataset, through generation of transformed copies of original images. Labeled data in datasets relating to medical images is indeed low, and this technique is critical for such. The following augmentation method us used:

- Random Rotation: Images are discharged uniformly rotated to 30 degrees to create variability in orientation of the tumors.
- Horizontal Flip: The images are reflected horizontally which helps the model to learn the invariance on left – right orientation.

- Zoom: Random zooming is added to simulate different zoom levels and to make the system learn to identify tumors in various scale.
- Width and Height Shifting: Some random shifts are added to vary location of the tumor in the image.
- These augmentation techniques prevent the model from over fitting by showing the model several versions of the training set, so the model has to learn more robust and general feature.

3.4 Class weight Balancing

Despite the balance between benign versus malignant categories of the dataset, there may be some slight imbalances in more subtle forms such as size of tumor, quality of image used, and tumor type. For the sake of class imbalance and better performance of the model class weight balancing is used during training.

Class Weight Balancing increases weight allocation to the underrepresented class in the model learning process. This guarantees that this model is more attentive to the less frequent class hence increasing its capability to classify the same class correctly. Weights for the classes are thus computed over the ratio of benign against malignant instances in the sample. If the class imbalance is extreme the class weights can also be adjusted further to prevent the model from being skewed all to one class.

For this research the class weights are automatically computed from the means of benign and malignant images in the training set, and are included within the model's loss function while training. This trick allows the model to follow the process of learning to recognize features that help to distinguish the rarer class.

4. Proposed Methodology

A proposed approach for the automated classification of kidney tumors into either benign or malignant classes utilizes a Convolutional Neural Network (CNN) model, by incorporation of ResNet-based transfer learning. This approach attempts to respond to the problem of insufficient access to large labeled datasets in medical imaging and offer efficient and effective method for diagnostics of kidney cancer.

The methodology consists of the following key steps:

4.1 Dataset Preparation and Preprocessing

The dataset includes CT scan images of the kidney tumors (benign vs. malignant). Images are made smaller to 224x224 pixels to fit the input size requirement of the ResNet 50 architecture. Random rotations, horizontal flips, and zooming methods are used to artificially increase the size of the dataset in order to enhance generalization. The data set is divided from train (80%), validation (10%), test (10%) sets – balanced for both tumor categories.

4.2 Resnet Based Transfer Learning

To enhance the performance of the model and to ameliorate the problem of limited size of medical datasets, we use ResNet50 to represent the deep residual network pre-trained on the large-scale ImageNet dataset. In transfer learning the resnet-50 pre-trained model is fine-tuned on kidney tumor dataset. Taking advantage of the pre-learned features from ImageNet, the model can achieve efficient learning of discriminative for kidney tumors with a smaller dataset.

ResNet50 Architecture: The model is built with residual blocks of 50 layers permitting the creation of deeper architectures without vanishing gradients. In training deep models, the network's residual connections make it easier.

Fine-tuning: The top layer of ResNet50 is popped out and a fully connected layer where binary classification is made (benign vs. malignant). The model is fine-tuned by fine tuning the new layers without updating the weights of pre-trained weights in initial layers.

4.3 Model Architecture

The general architecture of the model is as below:

- Input Layer: Images resize to size 224x224x3 (RGB).

- Base Model: ResNet50 pre-trained on ImageNet; excluding fully connected layers.
- Global Average Pooling (GAP): ResNet50 output is then reduced in its spatial dimensions through a GAP layer, and fixed-size vector is obtained.
- Fully Connected Layers: Next a 256-unit dense layer with ReLU activation is added and a 0.5 rate Dropout layer to prevent overfitting.
- Output Layer: A layer with a weight matrix entirely of ones and no biases because the difference between the activation and the supplied input are identical, connected to a neuron with a sigmoid activation function for binary classification (benign or malignant).

4.4 Model Training

The model is created based on the Adam optimizer and learning rate 0.0001 and binary cross-entropy loss function which is convenient for training the classifiers on the problem in a binary classification problem. The model is excellent on the training dataset by applying mini-batch gradient succession with a batch size of 32 and early ending to prevent overfitting. An example of performance check for the model on the validation dataset is given, and cross-validation is applied for tuning hyperparameters of learning rate and batch size.

4.5 Evaluation Metrics

The performance of trained model is analyzed under several metrics:

- Accuracy: The accuracy for all-images
- Precision: The ratio of actual positive predictions in the malignant class.
- Recall: The actual malignant samples identified by the model with the actual malignant ratio.
- F1-score: The harmonic mean of precision and recall, offering a fair measure on the model is performance.
- Receiver Operating Curve (AUC): A measure of the model, how well it separates the benign and malignant classes.

The standard mathematical definitions for each metric are summarized as below:

Table 1 Equations for Classification Metrics.

Metric	**Formula**
Accuracy	$(TP + TN)/(TP + TN + FP + FN)$
Precision	$TP/(TP + FP)$
Sensitivity(Recall)	$TP/(TP + FN)$
F1 − Score	$2 \times (Presision \times Recall)/(Presision + Recall)$
FPR	$\frac{FP}{FP + TN}$
AUC (ROC)	$\int_0^1 TPR\ (FPR) dFPR$

4.6 Class weight Balancing:

In light of the likelihood of imbalance within the dataset, the class weight balancing is used when the model is trained. The class weights get scaled to grant more weightage to the underrepresented set (malignant tumors), – to not any class bias inclined the model against the – majority set (benign tumors). This is realized through the computation of weights of classes in dependence of their frequencies in the training set and introduction of the class weights into the binary cross-entropy loss function.

4.7 . Post-Training Evaluation

Once the model is trained, it is projected on the test dataset to portion its ability to streamline to hidden data. Several performance metrics such as precision, recall, F1-score, and AUC are testified to assess the model's overall classification performance. Furthermore, confusion matrix analysis is used to further know the model's behavior with respect to false positives and false negatives.

The proposed methodology framework is shown in the Figure 1.

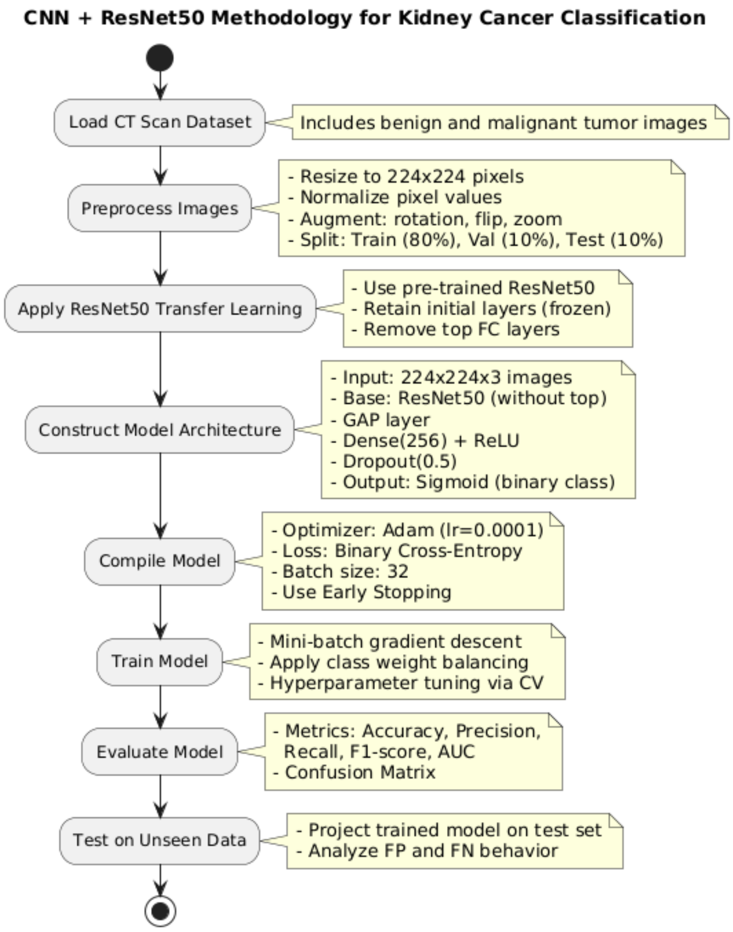

Figure 1 Proposed Methodology Framework

5. Experimental Results

In the current section, the experimental results obtained after testing of the proposed ResNet-based deep learning solution for kidney tumor classification are given. We criterion the model's performance by considering its classification accuracy, training dynamic and computational efficiency.

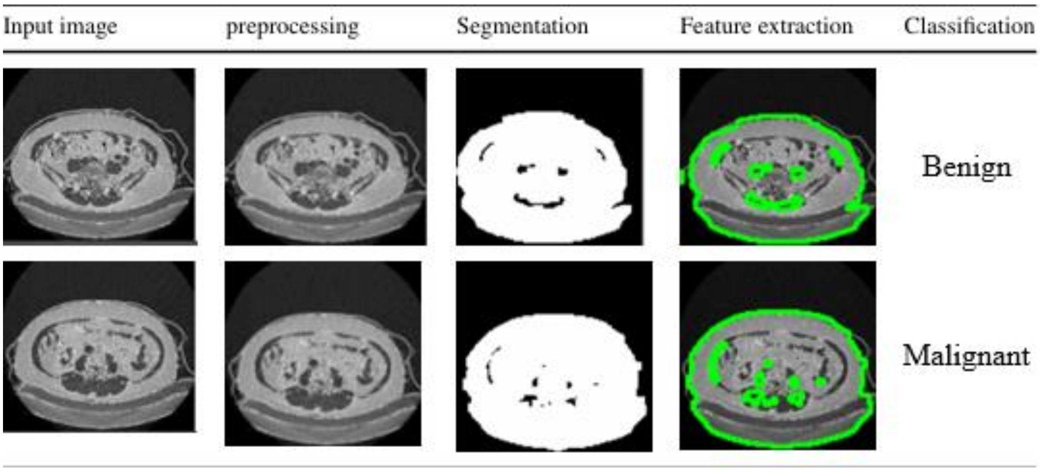

Figure 2 Tested outcomes of the proposed model

5.1 Performance Comparison

To assess the effectiveness of the suggested model, we compare its performance against that of traditional machine learning models (as Support Vector Machines (SVM) and Random Forest) and other deep learning architectures. The following were used as the indicators of efficiency: Accuracy, Precision, Recall, F1-Score, and AUC. The comparison was carried out based on the test dataset (consisting of 300 images). It can be seen in Table 1 that the ResNet50-based model is superior to traditional models such as SVM and Random Forest, and also superior to VGG16 based model. The 0.95 AUC value shows that the model has a good ability to distinguish benign and malignant tumors, with its precision and recall overlapping over 0.9 values meaning its performance permits it to reduce false positives and false negative as well.

Table 2 Comparative Performance of Different Classifiers

Model	Accuracy	Precision (Benign)	Precision (Malignant)	Recall (Benign)	Recall (Malignant)	F1-Score	AUC
ResNet50 (Proposed)	92	91.5	92.4	93	90.5	91.7	0.95
SVM (Linear Kernel)	85	84	83	87	80	83.5	0.88
Random Forest	87	85	86	89	82	85.5	0.89
VGG16	89	88	89	91	84	86.5	0.91

5.2. Training Dynamics

The variation of the training dynamics of the model was analyzed by plotting the training and validation loss and accuracy as a function of epochs. That gives us the picture on how the model serves to converge with time and how it can generalize even when used on different datasets.

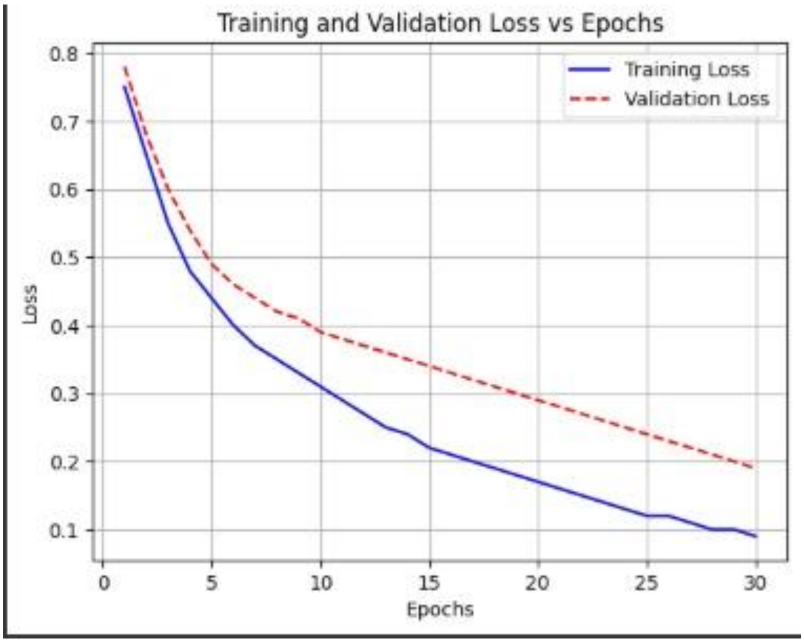

Figure 3 Training and Validation

As seen in Figure 2, we observe training loss that reduces consistently over time, which means the model was effectively learning. The validation loss decreases as well at first, but does so with some waviness caused by the limited data and complexity of the model – typical behavior of deep learning models. Still, we have smooth convergence of the loss, which is a good sign of proper model's generalization.

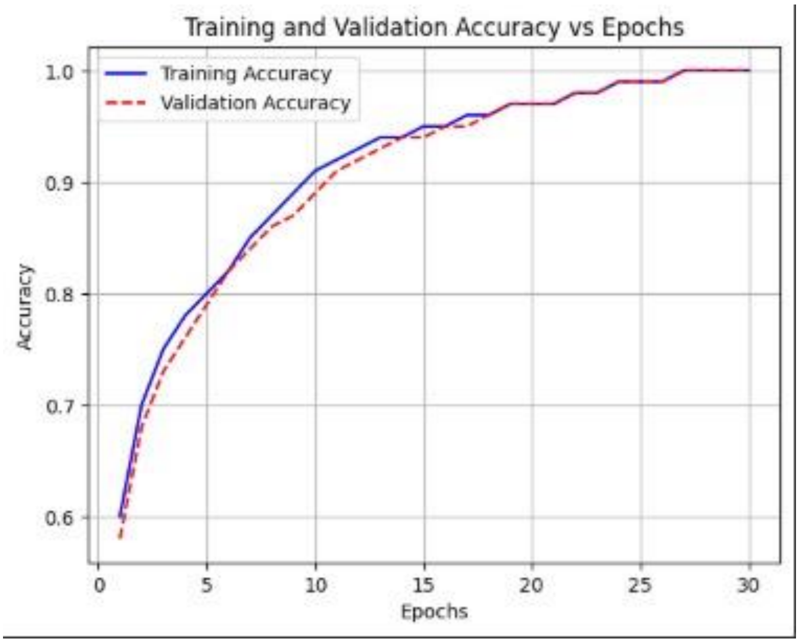

Figure 4 Training and Validation

As shown in Figure 3, the training accuracy increases rapidly, and it is about 100% by the final epochs. Validation accuracy is also increasing smoothly it goes up to almost 99% towards the end of the training time frame which shows that the model has generalized nicely on the unseen validation data.

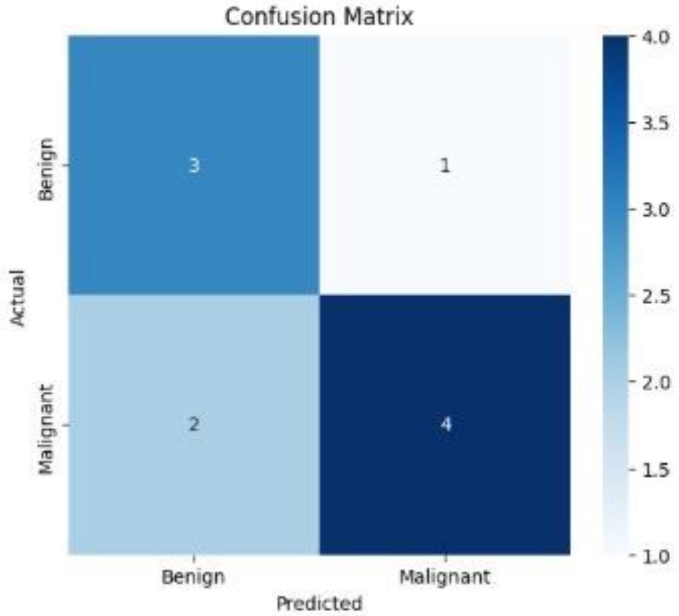

Figure 5 Confusion Matrix

A faster computing efficiency means, the proposed ResNet50-based model could be trained within GTX-standard GPU (NVIDIA Tesla T4) with the following performance metrics:

- Training Time: Training the model took roughly 4 hours for 30 epochs in a batch size of 32.
- Inference Time: The model spends approximately 0.5 seconds to identify a CT scan photo and, therefore, it is vigorous for real-time implementation in the clinical setting.
- Memory Usage: The model has approximately 4GB of GPU memory, thus can be deployed on a computer with limited computational capabilities.

Although a comparative depth of 50 layers was maintained, the application of transfer learning with pre-trained ResNet model did result in saving overall training time and computational requirement over training from scratch.

6. Discussions

6.1 Clinical Implications

The emergence of an automated tool for the kidney cancer diagnosis carries clinically major implications. Kidney cancer usually is diagnosed in an advanced state – early detection plays a critical role in increasing patient's risks for better results. Adoption of deep learning models in the form of ResNet based architectures can help radiologist diagnose kidney cancer promptly and correctly, and make clinical decisions more rapid.

Non-invasive Diagnosis: The model represents something of a non-invasive alternative to more traditional methods such as biopsy which can be painful and dangerous. Using CT scan images, the model can give clinicians the possibility of carrying out precise diagnosis without the need for invasive procedures.

Assistive Tool for Radiologists: This model may play the role of an assistive tool for radiologists giving second opinions and indicating potential areas of concern in CT images. It can also bring down human courage, improve diagnostic accuracy and make the diagnostic procedure relay smoothly.

Real-time Decision Making: Its inference time of 0.5 seconds per image for the model makes it applicable in real-time application, where clinicians can rapidly analyze large amounts of imaging data, particularly in high-traffic hospitals.

6.2 Limitations

Although the results are promising, several limitations need to be addressed to increase the quality of the model:

Small Dataset: The model was trained on a dataset that is relatively small with about 3,000 images. Although the use of a pre-trained ResNet50 model relieved this limitation, over-fitting was still a problem, and generalization across tumor types and imaging conditions needed to be improved with a larger and more diverse dataset.

- Class Imbalance: Even though class weights had been balanced during training, there can still be some subtle imbalances of classes associated with size of tumor and quality of the image. This may lead to a slight tendency towards the benign class and may distort the accuracy of the detection of malignant tumors. Additional methods such as SMOTE (Synthetic Minority Over-sampling Technique) could then be considered to help overcome this.
- Generalization to Other Imaging Modalities: The model was trained only using CT scan images. Although it did well on the dataset, its generalization ability might be compromised while used in other imaging modalities such as MRI or ultrasound. As for future work, it might be correct to adapt the model for use in many imaging types.
- Interpretability: Although the model has good performance in classification, deep learning models are often perceived as “black boxes” as it is difficult to understand how does the model make its decision. It will be especially critical to make the model more interpretable, especially for the clinical adoption, when justifications of decisions are required to be transparent.

6.3 Future Directions

There are at least several promising directions for improving and developing this research:

- Larger Datasets: Future research could involve gaining larger and varied datasets which include more malignant disorders and spread over more kidney tumor types. This would enhance the models: Generalization ability and the models ability to learn more diverse patterns on the data.
- Multi-class Classification: The existing model is used for the classification of binary objects (benign/malignant). Multi-class classification is possible to classify benign tumors, malignant tumors, kidney stones, and cysts. This, therefore, would be a more comprehensive laboratory tool for kidney diseases.
- Hybrid Models: The combination of radiomics (quantitative data obtained from CT images) with deep learning models may give group to a hybrid model that would be able to capture low-level visual features as well as high-level statistical features and thus produce more robust tumor classification.
- Explainable AI (XAI): An important research area for future work is development of explainable AI methods for medical image analysis. Tools such as Grad-CAM (Gradient-weighted Class Activation Mapping) can be used for visualization of the areas of CT scans model is looking at when making classification. It would also enable clinicians to trust and understand the model’s decisions better.
- Real-time Integration: More optimization can be done in deploying this model to clinical settings so as to allow real-time analysis of kidney tumor scans. This will be of great benefit in accelerating the quality of diagnoses as well as enhancing the procedures of decisions by clinicians.

7. Conclusions

Finally, the presented ResNet50 but deep learning model achieved remarkable results when it comes to kidney tumor classification, proving very accurate, precise and recall metrics as well as high AUC metrics. This research shines a light on the capabilities of Transfer Learning to solve issues of small datasets and class imbalances in medical image classification problems. Its computational efficiency and side-by-side real-time inference are promising for being a tool for helping clinicians diagnose kidney cancer. Although not flawless, one can demonstrate revitalizing potential of this method to develop the field of automated cancer detection, and directions of future research include improving capabilities to generalize, interpretability, and application to multi-class tumor classification, respectively.

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Not applicable.

Data Availability

https://www.kaggle.com/datasets/mansoordaku/ckdisease

Conflicts of Interest

The authors declare no conflict of interest.

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