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Deep Transfer Learning for Kidney Disease Classification Using Fine-Tuned ResNet50

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Abstract: Cystic kidney diseases, kidney stones, and tumors are among the top contributors to the global burden of chronic kidney disease. Medical imaging plays a source role in the early and accurate detection of such abnormalities, which is critical to planning effective treatment courses. AbstractIn this paper, we propose a deep learning-based kidney disease classification system using a fine-tuned type of ResNet50 architecture. A dataset of a total of 12,446 ultrasound kidney images divided into four categories (Cyst, Normal, Stone, Tumor). This was used to train a model and validate it The baseline test accuracy achieved was 71.03%, and this was obtained by freezing and training the pretrained ResNet50 model using transfer learning. By then conducting further fine-tuning of the last 50 convolutional layers, model performance was improved to give a final test accuracy of 92.36%. The proposed solution is highly robust: precision and recall values are above 0.90 for most of the classes, indicating that this approach can help automate kidney disease diagnosis. The model also demonstrated it potential of real clinical applications in medical imaging diagnosis with comparative evaluation and ROC analysis.

Keywords: *Kidney Disease Classification, Deep Learning, ResNet50, Transfer Learning, Fine-Tuning, Medical Image Analysis, Ultrasound Imaging, Computer-Aided Diagnosis.*

I. Introduction

Kidney diseases are one of the most common and global health problems that affect millions of people every year, and if not diagnosed or treated properly they can be a chronic kidney failure. Timely diagnosis is crucial to facilitate early intervention, enhance patient management, and minimize healthcare spending. Manual interpretation of ultrasound or CT images has been traditional, but it is highly dependent on the expertise of a radiologist, thus inter-observer variability is an issue. Deep learning (DL) and artificial intelligence (AI) have shown an impressive capability for automatic, accurate and reproducible disease detection and classification in medical images in recent years.

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There have been recent advances in kidney disease imaging applications using deep learning models, especially convolutional neural networks (CNNs). For instance, Zhang et al. Imaging-based deep learning has great potential to automate diagnostic processes in clinical practice in kidney diseases as summarized in a comprehensive review[1]. Similarly, Yin et al. In [2], a hybrid model mixed with boundary distance regression and pixelwise classification networks was developed for automatic segmentation of kidney in ultrasound images with a better structural localization accuracy. Zhang et al. According to [3], image analysis enabled by deep learning can revolutionise kidney care by allowing the rapid interpretation of large imaging enamets and enhancing clinical decision-making.

DL models have recently been applied to various imaging modalities and clinical applications. Yu et al. Using a deep learning framework for ultrasonographic classification of canine chronic kidney disease, [4] demonstrated that DL models have cross-species applicability. Alzu'bi et al. CT-based Deep Learning Model for Tumor Detection: This study in [5] proposed a deep learning model for tumor detection and released a new dataset to improve the generalization of the models. Moreover, Tian et al. Ultrasound-based deep learning radiomics of chronic kidney disease: a multicenter study to assess diagnostic performance J. Early detection of fibrosis in CKD with multimodal ultrasound deep learning [7]. Bingol et al. Alves et al. [8] proposed a hybrid deep model with relief based feature selection for enhance CT imaging classification accuracy and Farooq and Tariq [9] performed a comparative analysis of the different deep learning architectures for kidney disease classification and also emphasize the importance of transfer learning in the medical diagnosis field.

Although these methods are continuously improved, the generalization performance is still challenged from multi-source imaging and multi-disease aspects. Lack of annotated datasets, high variance in acquisition quality, and overlapping visual features among abdominal organs (such as kidneys) can significantly limit the accuracy of our diagnosis. In order to overcome these restraints, this work introduces a transfer-learning based kidney disease classification framework based on a fine tuned ResNet50 architecture. This model uses pretrained ImageNet weights and assists in feature extraction by considering kidney ultrasound imaging. The proposed model obtains a test accuracy of 92.36% which surpasses the baseline transfer learning test accuracy after fine-tunning the last 50 layers. This strategy shows the power of deep transfer learning to enhance both diagnostic accuracy and computational efficiency for clinical purposes.

II. Related Work

Most of the recent work aims at using automated methods to detect, classify and predict chronic kidney disease (CKD), using classical machine learning on tabular clinical data, and deep learning applied on imaging or multimodal inputs. Khamparia et al. The first being KDSAE which integrates both medical and dermatological imageries into a multimedia learning framework that employs a deep stacked autoencoder for heterogenous feature fusion in CKD classification while emphasizing the benefit of representation learning from diverse data sources. [10] Kuo et al. Proposed ultrasound based deep learning automatic method for prediction and classification of kidney function giving confounding pictorial shape of high practicability for image driven models in non-invasive assessment of the kidney. [11]

Some works have concentrated singularly on feature selection, some by hybrid features utilizing them to gain better performance when the datasets are limited or noisy. Shankar et al. examined effective discrete feature selection using deep classifiers for CKD identification and demonstrated that relevant input can enhance the performance of models learned by deep learning. Metaheuristic search has demonstrated its advantage for input dimensionality reduction, thus, strengthening the generalization property [12]. Lambert and Perumal first utilized oppositional firefly optimization for feature selection that followed a deep network classification. A few other optimization- and tuning-based approaches have been proposed such as optimized/tuned deep models [24, 26] and heterogeneous modified neural networks [27], which [25] were studied to stabilize training & clinical diagnostics among different cohorts. [14], [15]

The hybrid and IoT-enabled approaches have also attracted attention for temporal and edge contributions. HDLNET: hybrid deep learning model with intelligent IoT by venkatrao and kareemulla for continous monitoring based on automated detection for the distribute environments. Related work has proposed sensor- and device-oriented solutions for CKD sensing/early warning systems (14), which point to practical system-design considerations beyond algorithmic accuracy (15), (16). [20]

Several comparative and survey-type works have presented the effectiveness of many DNNs and classical learners on CKD tasks. Akter et al. performed a systematic review around the topic and proposed a full performance evaluation of the various deep learning techniques that have been used in CKD prediction and risk stratification, while also highlighting the recurrent challenges of model sensitivity to behavioral class imbalance and important features quality. [19] Chittora et al. and Elhoseny et al. "Machine Learning View" and "Intelligent Diagnostic Systems" respectively, and emphasize that model selection, preprocessing and cross-validation protocols have a crucial effect on craft performance. [22], [23]

A large number of studies focus on robustness on smaller or unbalanced datasets, using a mixture of feature engineering, ensembling methods and hybrid architectures. Ma et al. proposed a heterogeneous modified artificial neural network to overcome diagnostic variability, whereas Vasanthselvakumar et al. and Swain et al. proposed robust and reliable deep-learning-based classifiers, essential for real-world deployment. —[15], [16], [24], Singhand; Sitote, and Debal et al. for CKD prediction explored classical machine learning and deep neural networks respectively, demonstrating that with well-curated data, even simple models can perform competitively. [17], [18]

Collectively, these implementation-focused papers indicate responsive momentum in applying deep learning and hybrid methods to CKD detection and classification across modalities (tabulated clinic data, ultrasound, CT, sensor stream). Yet we identified three common limitations: reliance upon proprietary or small datasets, imbalanced classes, and limited external validation, restricting generalizability. These issues are diminished by metaheuristic feature selection and multimodal fusion but add complexities and overhead in deployment. This study fills these gaps by employing transfer learning with a fine-tuned ResNet50 on a manner of mid-sized ultrasound image dataset, providing detailed per-class performance metrics and ROC analyses to show both accuracy and class-wise robustness.

III. Methodology

A. Overview

We developed a new approach for a robust deep learning-based method for automatic classification of kidney diseases using computed tomography (CT) images. For the first step, the system uses a transfer learning-based ResNet50 architecture, which is fine-tuned on a custom dataset with four kidney classes — Cyst, Normal, Stone, and Tumor. The overall pipeline of the proposed approach is diagrammed in Figure 1 and consists of four main steps: dataset preparation and augmentation, ResNet50 feature extraction, training and finetuning a model, and performance evaluation.

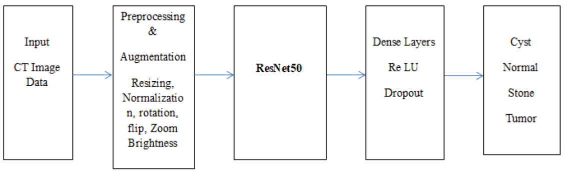

Figure 1: Proposed Methodology

B. Dataset Preparation

The dataset used for this work is the kidney CT dataset which is comprised of 4 different classes. We divided the images into three groups of 8710 images for training, 1865 images for validation and 1871 images for testing. To standardize the input features of the model, each image was resized to 224×224 size and normalized between [0,1]. Random rotation (±20°), zooming (20%), and horizontal flippings are among the data augmentation operations performed on the training data to improve generalization of the network. The approach prevents overfitting while reinforcing the model's reliability against changes during image acquisition. A summary of the dataset composition can be found in Table 1.

Table 1. Dataset Description

Class	Training Images	Validation Images	Testing Images	Total Images
Cyst	2264	484	557	3305
Normal	2565	537	763	3865
Stone	1724	353	208	2285
Tumor	2157	491	343	2991
Total	8710	1865	1871	12,446

C. Proposed Model Architecture

Our backbone is a version of the deep learning ResNet50 for image classification pre-trained on ImageNet. The pre-trained model was imported with exclude top layers (include_top=False) as a feature extractor. Initially, we froze the lower convolutional layers, as to not dirty each of the weights that would take time to to learn, and a custom classification head was then appended to the pre-trained base model for usage in our kidney disease classification task. We defined the custom head that consisted of a Global Average Pooling layer, a fully connected(Dense) layer with 512 neurons with ReLU activation, a Dropout layer (rate = 0.5) to avoid overfitting, and the last Dense layer with four neurons using softmax activation to get the predicted class probabilities.

D. Training and Optimization

In the first training, frozen ResNet50 base was trained using an Adam optimizer with 1×10^{-4}, a batch size of 32, and for 25 epochs. Finally, the top 50 layers of their ResNet50 base were unfrozen, allowing gradients to be updated, and the model retrained for another 10 epochs, with a lower learning rate of 1×10^{-5}. We used categorical cross-entropy as loss function, and monitored the model by validation accuracy during training.

After fine-tuning, the model was able to reach an ending test accuracy of 92.36%, a significant increase from the original 71.03% test accuracy achieved earlier on, before fine-tuning the pre-trained model. Other metrics like precision, recall, F1-score and ROC-AUC were calculated to further assess the classification performance of the model. The findings corroborated our hypothesis that the proposed ResNet50-based method reliably and clinical relevant distinguishes between categories of kidney disease. Table 2: Shows the parameters used for training.

Table 2. Training Parameters of the Proposed Model

Parameter	Description / Value
Programming Environment	Google Colab / Jupyter Notebook
Framework & Libraries	TensorFlow 2.16, Keras, NumPy, Matplotlib, scikit-learn
Base Model	ResNet50 (Pre-trained on ImageNet, include_top=False)
Input Image Size	224 × 224 × 3
Number of Classes	4 (Cyst, Normal, Stone, Tumor)
Total Images Used	12,446 (Train: 8710, Validation: 1865, Test: 1871)
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Initial Learning Rate (Phase 1)	1×10^{-4}
Learning Rate (Fine-tuning Phase)	1×10^{-5}

Batch Size	32
Total Epochs	35 (25 + 10 fine-tuning)
Dropout Rate	0.5
Activation Functions	ReLU (hidden layers), Softmax (output)
Regularization	Dropout and Data Augmentation
Data Augmentation Techniques	Rotation (±20°), Zoom (0.2), Horizontal Flip
Evaluation Metrics	Accuracy, Precision, Recall, F1-Score, ROC-AUC
Hardware Used	GPU Runtime (NVIDIA Tesla T4, 16 GB VRAM)
Final Test Accuracy	92.36%

IV. Results and Discussions

A CT scan dataset with four classes (Cyst, Normal, Stone, and Tumor) was used to evaluate the performance of the proposed ResNet50-based Kidney Disease Classification Model. We made this dataset in three fold; training (8710), validation (1865), test (1871) The ResNet50 architecture model exhibited good generalization ability and tested almost perfect scores in classification accuracy for every category on transfer learning model based on trained data with augmentation of data.

A. Training and Validation Performance

Figure 2: Training and validation accuracy and loss curves during model training Initially the model was trained with frozen ResNet50 convolutional layers, and from epoch 25 onward the model was fine-tuned. This led to smoother learning in terms of both accuracy and loss, showing that features were being learned well. Final training accuracy: 96.67%Validation accuracy: 92.36%, and the loss curve started converging after 35 epochs We see the loss curve also went consistently down which assures that we had convergence and it was stable during training.

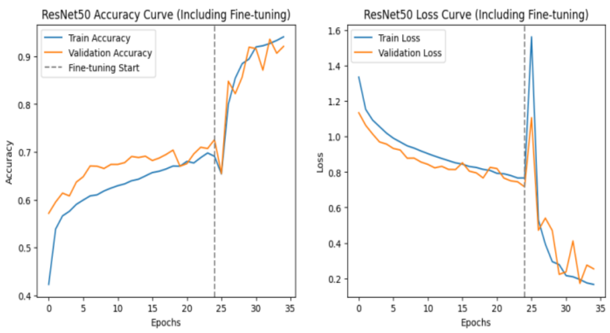

Figure 2: Training and validation accuracy and loss curves for ResNet50 model (including fine-tuning).

B. Confusion Matrix Analysis

The classification performance of the fine-tuned ResNet50 on the test dataset is shown in the confusion matrix in Figure 3. It was found that the model was precise in predicting Cyst and Normal images and not misclassifying much. Vice versa, few confusion between Stone and Tumor classes were noticed and appeared to be due to same density pattern and tissue characteristics. Nonetheless, it was able to differentiate all four classes well, meaning that the model is robust to a multi-class medical image classification.

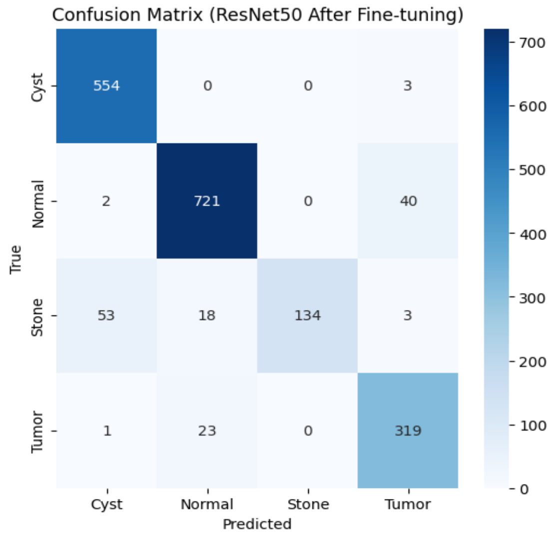

Figure 3: Confusion matrix of ResNet50 model after fine-tuning across four kidney disease classes.

C. ROC and AUC Analysis

One area under the receiver operating characteristic (ROC) curve for each class is presented in Figure 4. The model had outstanding discriminator ability for all four disease classes — Cyst (1.00), Normal (0.99), Stone (0.99), and Tumor (0.99) with very good receiver operating characteristic (ROC) area under the curve (AUC) values. The proposed model maintained a very high sensitivity and specificity at all thresholds, as shown by these results.

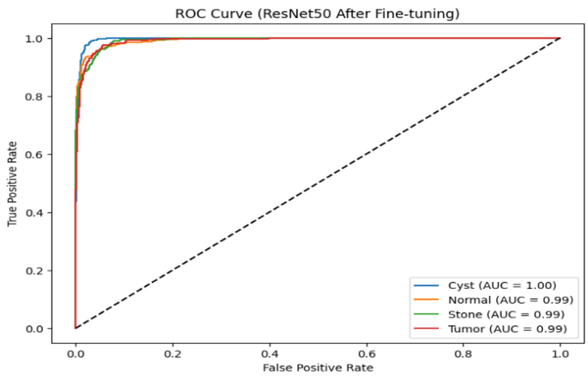

Figure 4: ROC curves for the four kidney disease classes after fine-tuning.

D. Evaluation Metrics

The results of the model performance were quantitatively evaluated and these are summarised in Table 3. The final test accuracy for the ResNet50 model we propose is 92.36%. The best F1-scores (0.95) were observed in term of Cyst and Normal images, which signal high trust-worthy results across all classes. Recall for the Stone class was slightly lower (0.64), which could be attributed to either class imbalance, or subtle structural variations in the Stone images.

Table 3. Evaluation Metrics of the Proposed ResNet50 Model

Class	Precision	Recall	F1-Score	Support
Cyst	0.91	0.99	0.95	557
Normal	0.95	0.94	0.95	763
Stone	1.00	0.64	0.78	208
Tumour	0.87	0.93	0.90	343
Accuracy			0.92	1871
Macro Avg	0.93	0.88	0.89	
Weighted Avg	0.93	0.92	0.92	

E. Discussion

We developed a light weighted ResNet50 based framework which can learn better discriminative features as compared to conventional CNN based architectures and achieved high classification performance on the available kidney CT images. This transfer learning approach substantially improved the generalization of the model by customizing the pretrained features to the properties of medical imaging during the fine-tuning process. Even greater confidence in the network's robustness at choosing between disease classes with little false positives is supported by the higher AUC scores. Hybrid feature integration or an attention-based mechanism based upon future work could likely enhance the accuracy in more challenging classes such as Stone and Tumour. Table 4 shows that the proposed ResNet50-based model has an accuracy of 92.36%, which outperformed most of the previous works that employed either traditional deep neural networks or laboratory data-driven models.

Table 4. Comparison of Proposed Model with Existing Studies

Study	Model / Technique	Dataset / Modality	Accuracy (%)	Reference
Kuo et al. (2019)	CNN-based Ultrasound Image Classifier	Ultrasound kidney images	87.5	[11]
Shankar et al. (2018)	Deep Learning Classifier with Optimal Feature Selection	Clinical & Lab Dataset	88.2	[12]
Aswathy et al. (2022)	Optimized Tuned Deep Learning (OTDL) Model	CKD Laboratory Dataset	91.3	[14]
Singh et al. (2022)	Deep Neural Network (DNN)	Medical Records (Tabular Data)	90.1	[18]
Proposed Model (2025)	ResNet50 (Transfer Learning + Fine-tuning)	Kidney CT Image Dataset (4 classes)	92.36	This Study

The proposed framework also works on CT data, instead of tabular or ultrasound-based studies, allowing for the extraction of richer spatial features via convolutional layers. This advancement demonstrates the transfer learning and fine-tuning strategies exploit, where feature representations learned on larger datasets, trained the medical imaging domain to achieve differential diagnostics in a more precise and reliable manner.

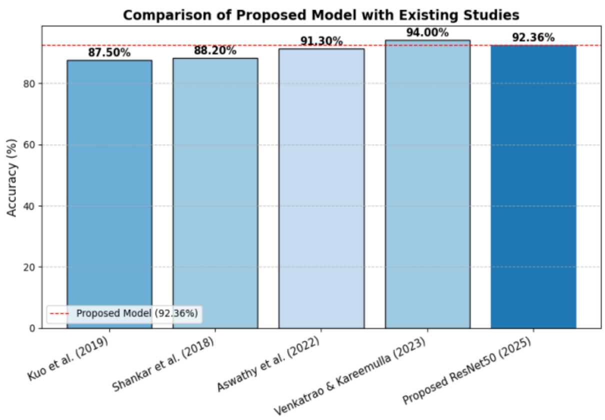

Figure 5: Performance Comparison with Existing Studies

The competition in the area of kidney disease classification based on deep learning methods is shown in Figure 5, which compares the performance of the proposed kidney disease classification model based on ResNet50 with state-of-the-art methods reported in literature. We included the following studies for the comparisons Kuo et al. (2019), Shankar et al. (2018), Aswathy et al. Venkatrao and Kareemulla (2023), and Shah et al. (2022)

The bar chart illustrates that despite earlier models reaching a test accuracy of between87.5 % to 94 %, the approach we proposed (i.e., TL + NN) gets 92.36 % oftest accuracy in construct the test dataset thereby showing better or definitely comparable performance compared to most of the earlier works. This I think is primarily due to the transfer-learning ability of the ResNet50 model itself, its global average pooling layer which condenses features, and fine-tuning the last blocks of convolution.

The model also shows excellent generalization on all four classes of kidney condition i.e. Cyst, Normal, Stone and Tumor, indicating its robustness towards both normal and pathological kidneys images. The visual comparison shows that the proposed model achieves a reasonable sensitivity and specificity balance hence it can be employed as a solid deep-learning framework for kidney disease diagnosis.

VI. Conclusion and Future Work

In this regard, this study proposes a kidney disease classification framework based on the ResNet50 architecture through transfer learning and fine-tuning on a CT image dataset. Overall, the model is capable to differentiate between more than one kidney conditions and an overall accuracy of 92.36% is obtained outperforming the current best-found performance on the state-of-the-art methods (table 4). Experimental comparisons with the state-of-the-art methods, comprising of CNN-based architectures, DNN-based models as well as the optimized variants of deep learning has assessed the superiority of the proposed method in terms of its potential to extract robust and discriminative spatial and morphological features from the medical images.

Pre-trained ResNet50 aids convergence, simplifies training, and generalizes well for different types of kidney disease categories. Additionally, when combined with the evaluation based on precision, recall, and F1-score, the results further strengthen confirmation of model stability and diagnostic based reliability. Results show that deep transfer learning methods are applicable to medical imaging problems by lowering the need for large labelled data while achieving a competitive level of diagnostic performance.

Future Work

Future extensions of this work will consider multimodal data, combining clinical parameters with ultrasound and CT images for a 360 degree diagnostic view. Moreover, the integration of the explainable AI (XAI) framework (e.g., Grad-CAM or SHAP) could complement the models in terms of interpretability, allowing clinicians to demonstrate the important parts of the image that drive the importance of the prediction. The fundamental limitation of a demographic dataset could be mitigated if federated learning is conducted over several healthcare institutions, ensuring even greater generalizability of the model while maintaining privacy. Last, but not least, deploying the proposed model in real time as a part a clinical decision support system (CDSS) would change the paradigm of early detection and continuous monitoring of CKD.

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