An Effective Approach for Kidney Diseases detection using Transfer Learning

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ABSTRACT:
An essential issue in public health, chronic kidney disease is characterized by a high prevalence, morbidity, and mortality rate. India is home to 17% of the world's population, but having less than 3% of the total land mass. Results have been less than ideal due to a combination of factors, including a low gross domestic product, a large percentage of patients living below the poverty line, and inadequate funding for health care. In addition, despite ongoing concerns about communicable diseases, high rates of child and maternal mortality, and a competition for resources, chronic kidney disease (CKD) and other non-communicable diseases have frequently been disregarded. High prevalence of chronic kidney disease in India is due to multiple factors. According to data from the United Nations Children's Emergency Fund, 28% of infants weigh less than 2.5 kg when they are born. Reduced estimated glomerular filtration rate and reduced kidney volume at delivery may result from nutrients deficiency during pregnancy, such as hypovitaminosis A.A GFR of 60 or above is considered normal. Consult your physician regarding the reevaluation of your GFR(Glomerular Filtration Rate).GFRs below 60 may signify kidney pathology. Inquire with your physician on the preservation of kidney health.A GFR of 15 or lower indicates renal failure. Dialysis or kidney transplants are necessary for the majority falling below this threshold. Consanguinity and genetic inbreeding enhance kidney and urinary tract congenital abnormalities and obstructive or reflux nephropathy risk. Poverty, poor sanitation, pollution, water contamination, overcrowding, and known and unknown nephrotoxins (including heavy metals and plant poisons in indigenous treatments) can cause glomerular and interstitial kidney disorders. The rising prevalence of hypertension and diabetes compounds these exposures. India is anticipated to have the most diabetics by 2030.

Introduction

Chronic kidney disease (CKD) is renal impairment caused by kidney failure to filter blood. The kidneys filter blood and excrete waste and surplus water via urine.CKD is the largest cause of death and disability worldwide, according to the Worldwide Impact of Disease shown in Fig. 1. Deaths caused by chronic kidney disease (CKD) rose by 41.5% worldwide between 1990 and 2017, while the frequency of the disease rose by 29.3% across all age groups [1]. Between 2001–03 and 2010–13, the percentage of fatalities in India caused by renal failure rose by 38% [2]. The primary cause of premature deaths and disability-adjusted life years is cardiovascular disease (CVD), and chronic kidney disease (CKD) is a major risk factor for this illness. Developing nations, such as India, frequently fail to take advantage of opportunities for secondary and tertiary prevention of chronic kidney disease [3]. Typically, patients wait until symptoms appear before seeking medical help, which is sometimes rather late in the progression of a disease. Early detection of chronic kidney disease (CKD) is possible only by examination of kidney function in the context of other medical issues or, less frequently, as part of regular screening [4]. It is evident that risk factor identification and mitigation methods in chronic kidney disease (CKD) can only be internationally effective if they address the specific issues faced by regions with poorer socio-demographic indices, since this is where the majority of CKD cases occur[8].In cases of chronic kidney disease (CKD), waste products build in the body, resulting in symptoms such as back pain, diarrhea, epistaxis, fever, rash, emesis, and stomach discomfort. The cumulative deterioration would impact the entire human body and result in the onset of various illnesses. As the disease progresses and attains its terminal phases, it may result in demise.

Several studies have used Support Vector Machines, Artificial Neural Networks, Deep Neural Networks, an Ensemble method, Extra tree, Random Forest, and Logistic Regression to detect chronic kidney disease early [1, 4,8]. Decision Trees, Random Forest, LightGBM, Logistic Regression, and CNN are also used for early detection [9].

Figure 1: Sample of kidney Dieses images

Moreover, it is evident that contemporary society is increasingly emphasizing recommendation systems. Users anticipate that the system will propose superior options.

A recommendation-capable system must possess the capacity to make autonomous decisions. To make a judgment independently, one needs possess classified facts.

All the aforementioned factors prompted our interest in conducting this type of research-based activity.

1 Related Work:

The Adaptive Hybridized Deep Convolutional Neural Network (AHDCNN) is introduced for early CKD prediction and diagnosis [1]. Kidney cancer CT scans are analyzed using a deep learning system to identify lesion subtypes. The median value estimate will replace missing values in the initial data analysis. The noise-free data is used to extract kidney disease-related properties for the classifier to detect kidney pattern discrepancies [1].

This study presents an innovative deep learning model that integrates a fuzzy deep neural network (FDNN) for the identification and forecasting of renal illness. The findings indicate that the suggested model achieves an accuracy of 99.23%, surpassing current methodologies [2]. This study introduces an innovative deep learning model that integrates a fuzzy deep neural network (FDNN) for the identification and forecasting of renal illness. The findings indicate that the suggested model achieves an accuracy of 99.23%, surpassing current methodologies [3].The combination of fusion with graph embedding addresses the issue of imbalanced class frequency and demonstrates superior classification accuracy. The technique is applicable to different medical issues. It may be utilized in clinical and hospital environments to assess cardiac and renal function during different phases of patient management [4].SVM and ANN are popular machine learning methods[13, 14]. Both solutions are beneficial and perform well in several domains. Artificial Neural Networks (ANN) have been introduced as a novel model for CKD prediction and compared to Support Vector Machines (SVM), which had the highest accuracy in past studies [11]. The dataset was preprocessed to replace missing values. The training and test datasets were divided 90:10 using 10-fold cross-validation. Support Vector Machine and Artificial Neural Network parameters were optimized. Both methods were tested with different parameters. Using optimized features, the ANN performed best with 99.75% accuracy, while the SVM performed best with 97.75% [5].

Here author introduces a complete image fusion framework employing convolutional neural networks, which provides four key advantages over existing image fusion models: Our model is fully convolutional, facilitating end-to-end training without the need for post-processing methods. They methodically created an extensive multi-focus image collection by producing partially-focused images with random depth variations derived from the RGB and depth images of the NUY-D2 dataset to thoroughly train our algorithm. Further-more, instead of lacking ground truth or employing focus maps as ground truth in existing datasets, the source RGB images from the NYU-D2 dataset inherently serve as the ground-truth fusion images for our multi-focus image dataset, which is crucial for enhancing the fundamentally regressed image fusion models. This model, created within the framework of transform-domain image fusion, exhibits superior generalization capabilities for integrating diverse image types without necessitating fine-tuning, surpassing current image fusion models. This represents the first application of perceptual loss to augment image fusion models, enabled by the pres-ence of ground-truth fusion images, hence producing fusion images with improved texture detail. The com-prehensive experimental findings across four categories of image datasets demonstrate that the proposed model shows enhanced generalization abilities for integrating various image types relative to existing models, producing fusion images that are comparable to or surpass those generated by resulting image fusion algo-rithms, without requiring finetuning on additional datasets [6].

Here author examines the relationship between data components and the attributes of the target class and developed a series of predictive models utilize machine learning and predictive analytics, facilitated by en-hanced attribute measurements achievable through predictive modeling. This study begins with 25 variables alongside the class characteristic, ultimately refining the selection to 30% of those factors as the optimal sub-set for identifying CKD. Twelve distinct classifiers based on machine learning have been evaluated in a su-pervised learning context. In a supervised learning framework, twelve distinct machine learning classifiers were evaluated, with the XgBoost classifier achieving the highest performance metrics: an accuracy of 0.983, precision of 0.98, recall of 0.98, and an F1-score of 0.98[7].The Gradient Boosting (GB) and Random Forest (RF) models obtained 89.61% accuracy in diabetes prediction, whereas the hybrid LSTM-CNN model beat other DL methods with 89.7% accuracy. The RF model predicted renal illness with 97.5% accuracy, whereas the LSTM-CNN model achieved extraordinary accuracy of 98.9%[8].

This study involved acquiring and annotating a substantial dataset of 12,446 CT whole abdomen and urogram images, focusing on kidney stones, cysts, and tumors, the predominant forms of renal pathology. The dataset categorised into four classifications: cyst, tumor, stone, and normal shown in Fig. 2. Data was gathered from many hospitals in the Dhaka region. This study introduces a novel and adaptable platform for the clinical diagnosis of renal conditions, including tumors, calculi, and cysts. The improved accuracy of YOLOv8 model facilitates the identification of kidney cysts, stones, and tumors. They utilized metrics such as accuracy, precision, recall, F1 score, and specificity to assess its performance. The network achieved an accuracy of 82.52%, precision of 85.76%, recall of 75.28%, F1 score of 75.72%, and specificity of 93.12%[9].

With an accuracy of 0.993 and 0.992 for the half yearly and yearly data predictions respectively, the deep ensemble model performs more effectively than all other models[10].

2 Dataset

The ability to learn to analysedata without the need for explicit programming is the essence of machine learning, an AI technique. The program's stated goal is to train programmers to be flexible in the face of changing data. It operates either under supervision or without it. Frameworks that satisfy their aims are creat-ed by combining the proper elements. Parametric modeling, multi-dimensional and multi-classification prob-lems, predictive clustering, and similar efforts are examples.

The dataset includes patients from multiple hospitals in Dhaka, Bangladesh, diagnosed with kidney tu-mors, cysts, normal conditions, or stones shown in table 1. Coro-nal and axial slices selected from both con-trast and non-contrast studies in accordance with the protocol for the whole abdomen and urogram. The Dicom study systematically curated one diagnosis at a time, leading to a compilation of DICOM images relevant to each radiological finding in the region of interest. Subsequently, the DICOM images were converted to a lossless JPEG format. Following the conversion, each image detection re-evaluated by a radiologist and a medical technician to confirm the accuracy of the data.

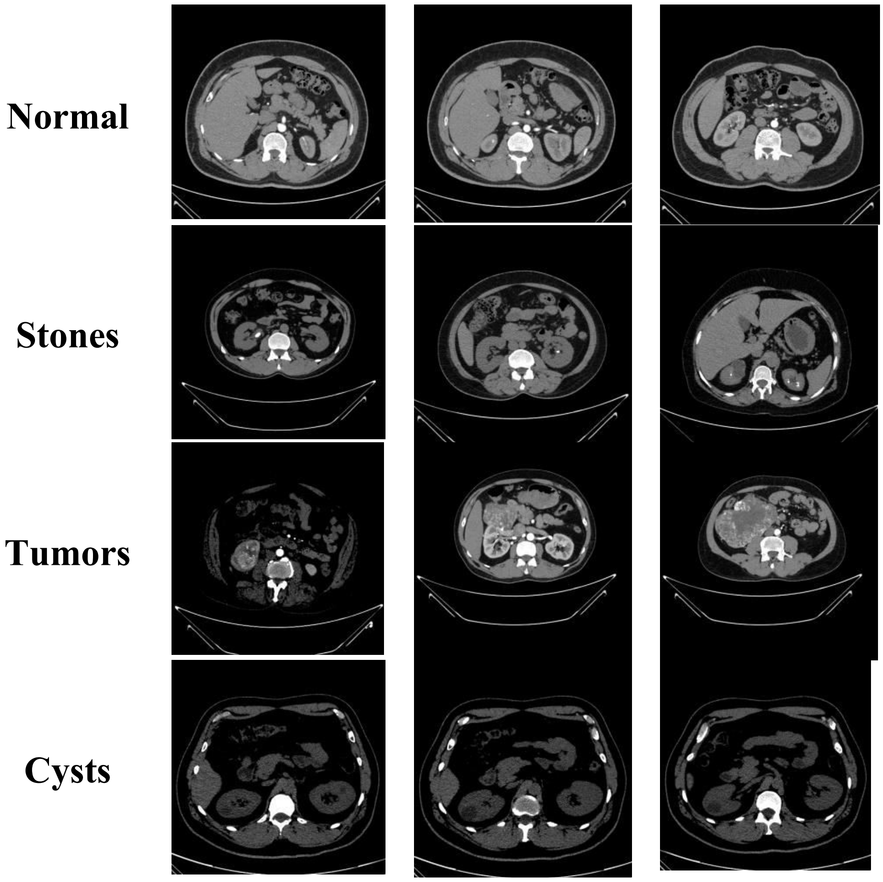

Figure 2: SampleCT-Scans Showing Tumors in Kidneyfrom CT-KIDNEYDataset

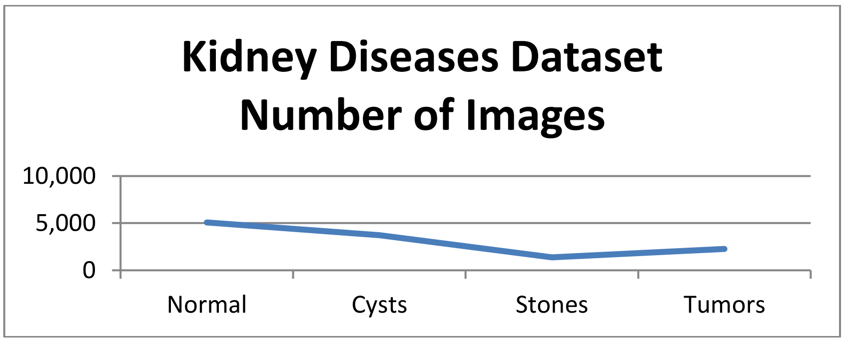

Figure 3:Graph Distribution of classes in dataset

Fig. 3 represents thedifferent class (normal, stones, tumors and cysts) of CT scan kidney images.

Table 1: Kidney Diseases Dataset[15]

Kidney Diseases Dataset	
Kidney Condition	**Number of Images**
Normal	5,077
Cysts	3,709
Stones	1,377
Tumors	2,283

Table 1 shows the actual figure of different class (normal, stones, tumors and cysts) of CTscan kidney images.

3 Proposed Work:

Image Processing

Real-world datasets nowadays, particularly clinical datasets, are vulnerable to missing, noisy, redundant, and inconsistent data. Working with poor data produces poor results. In order to prepare the dataset for the modeling stage, the first step in any machine learning application is to examine and comprehend the dataset's properties. Data pre-processing is the term used to describe this procedure.

Image Augmentation

Image augmentation is the predominant method employed to mitigate overfitting during the training phase of deep neural networks [20]. Image augmentation does not affect the semantic significance of the images. Training the network on a more extensive augmented dataset improves the robustness and generalizability of deep neural networks to unfamiliar inputs. Augmentation is employed to enhance the quantity of image samples in the dataset and introduce diversity. The data augmentation methods enhance and expand the data, allowing the model to function more efficiently and precisely.

By integrating transformations onto datasets, data augmentation approaches lower operating expenses. The augmentation methods used in this study include horizontal and vertical flips as well as a hybrid of the two. Constipation and generalized weakness are common symptoms of chronic kidney disease (CKD)[16], which lowers quality of life and increases chance of death.

Proposed Ensemble Transfer Learning Models:

The subsequent phase involves the formulation of the deep learning model, encompassing the selection of model architecture, model training, and hyperparameteroptimization through model validation.Diverse deep learning architectures emerge for medical image processing, many of which are constructed from convolutional neural networks (CNNs)[12]. The Convolutional Neural Network (CNN), originally created for image processing, is a significant modification of the Multilayer Perceptron, the most basic kind of deep neural network.

This study proposes an Inductive transfer-based new ensemble using model VGG16. Training deep neural network models from beginning requires an enormous quantity of labeled training data, which presents significant challenges in medical image detection; this issue has been addressed through the use of transfer learning and image augmentation techniques [16, 19].

Evaluation of predictive models

Developing an accurate machine-learning model requires performance evaluation. Assessing the prediction model's suitability for the dataset and performance on unknown data is necessary [17]. The performance evaluation evaluates a model's generalization accuracy on unseen or out-of-sample data. Cross-Validation (CV) partitions data to evaluate and compare models [20]. The initial dataset was divided into k folds, or equal-sized subsamples: nine for model training and one for validation. The average performance is recorded after k iterations. This study used tenfold cross-validation. Calculated performance measures include accuracy, precision, recall, F1-score, sensitivity, and specificity.

- **True positive (TP)**: This mentions to the scenario in which both the actual value and the forecasted value are positive.
- **True negative (TN)**: This refers to the scenario in which both the actual value of the data point and the prediction are negative.
- **False positive (FP)**: This denotes to instances where the true value of a data point is negative, while the prediction is positive.
- **False negative (FN)**: These mentions to instances where the true value of a data item is positive, while the prediction is negative.

Accuracy

Accuracy is the classification algorithm's ability to predict dataset classes. It measures how close the anticipated value is to the real or theoretical value [15]. Prediction accuracy is the ratio of correct forecasts to total occurrences. The accuracy equation is shown in below Equation.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$

Precision

Precision is the measurement of the true values that were accurately forecasted from the total predicted values in the actual class. Precision quantifies the classifiers' capacity for preventing labelling a negative example as positive. The precision equation is shown below.

$$Precision = \frac{TP}{TP + FP}$$

F-measure

F-measure (F1-score) is the harmonic mean of recall and precision. F1-score equation is shown below.

$$F1_{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

Sensitivity/Specificity

Specificity is often referred to as the True Negative Rate. It measures the proportion of accurately categorised negative values. The sensitivity is also known as specificity its equation is shown below.

$$Specificity = \frac{TN}{TN + FP}$$

Table 2: Results of experiment.

Model	Accuracy
VGG16	99.81
VGG19	99.61

Experimental Results:

Here apply VGG16 model on our dataset and achieved a training accuracy of 99.81%. However, we also obtained a loss of 0.75 during the training process, as shown in Fig.4 and 5 respectively.

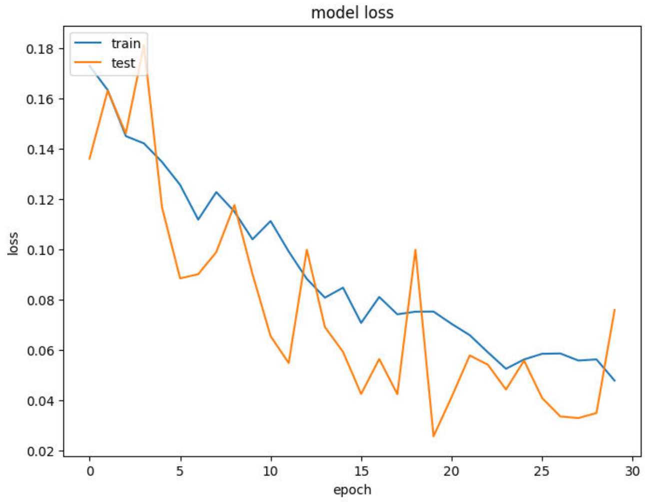

Figure 4:Training loss result of CT-KIDNEY-dataset

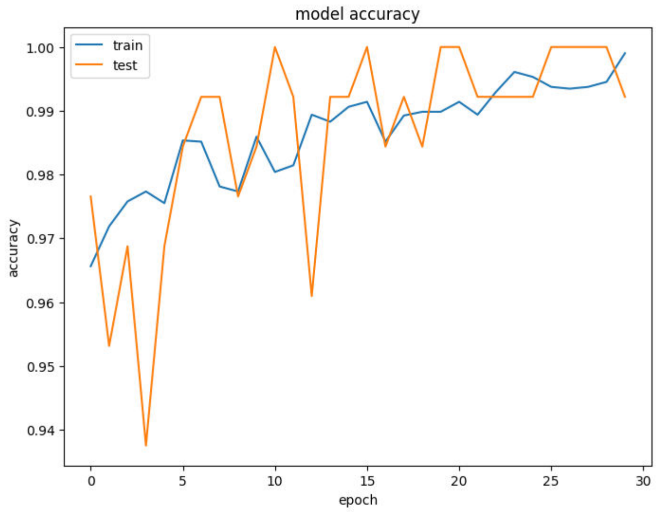

Figure5:Training accuracy result of CT-KIDNEY-DATASET

This strategy employs a fine-tuning approach, prompting a comparison with other fine-tuned models derived from pre-trained deep learning models (Table 2). To execute fine-tuning on pre-existing models [18], here employ settings analogous to those utilized in our methodology. Subsequently, VGG19 applied, yielding an accuracy of 99.61 and a loss of 0.1101 shown in Fig. 6 and 7.

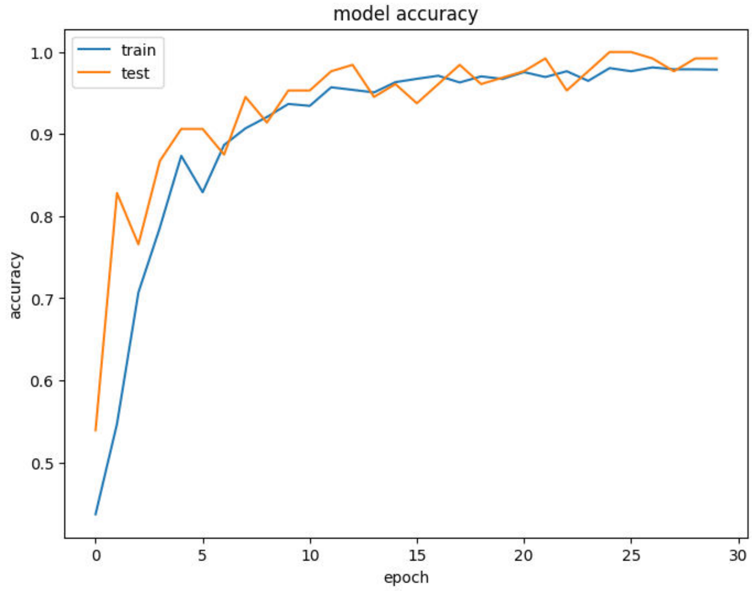

Figure 6: VGG19 after training accuracyof CT-KIDNEY-DATASET

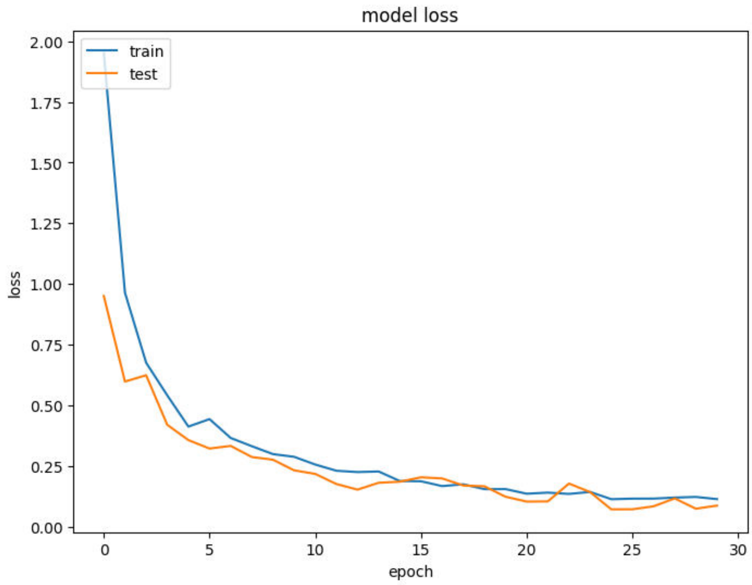

Figure 7: VGG19 after training loss

Conclusion:
This study suggests that data analytics may help predict occurrences, perhaps affecting current events. Chronic kidney disease is a widespread condition, and its frequency is increasing globally. Timely diagnosis based on the detection of proteinuria or diminished estimated glomerular filtration rate may facilitate early man-

agement to mitigate the risks of cardiovascular incidents, renal failure, and mortality linked to chronic kidney disease. In industrialized nations, screening for the disease is most effective when directed at high-risk populations, particularly the elderly and individuals with comorbid conditions. It has been used to predict chronic kidney disease risk in healthcare. This study aims to define CKD prediction. The VGG16 transfer learning model outperforms all other predictive models, with an accuracy of 99.81% data predictions. Therefore, before deep learning can effectively support clinical work, several aspects still need to be addressed.

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