Deep Learning Techniques for Chronic Kidney Disease Diagnosis

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ABSTRACT: Chronic Kidney Disease (CKD) is characterized by a progressive loss of kidney function, which can ultimately result in kidney damage or failure. As the condition advances, it becomes increasingly challenging to diagnose. Some doctors are looking forward to advancements in technology that can scan a patient's body and analyze their diseases. Leveraging data from routine clinical visits to assess different stages of CKD can facilitate early detection and timely treatment. Deep learning has the potential to make many things in the world seem possible, even causing surprise with its capabilities. In this study, we propose a deep learning-based framework for the diagnosis of CKD. Deep learning technology has opened up new possibilities in the medical field, often delivering results that exceed expectations. The dataset used was sourced from the Deep Learning Repository of the University of California, Irvine (UCI). Various deep learning algorithms, including Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNNs), MobileNet, and models specific to kidney disease, were implemented. Among these, the Random Forest classifier delivered the highest accuracy, highlighting the effectiveness of our method in segmenting medical images related to kidney and tumour analysis.

Key Words: Chronic Kidney Disease**,** Deep Learning**,** CNN, Mobile Net, Random Forest**,** Segmentation**,** Recurrent Neural Networks (RNNs).

1. INTRODUCTION

Kidneys are essential glands in the body's urinary tract because they excrete toxins from the circulatory system, regulate the equilibrium among body electrolytes and fluids, regulate blood sugar levels, and participate in the production of hormones. It maintains the human body's water and electrolyte equilibrium by releasing and purifying waste .It additionally secretes a variety of proteins and aids in controlling high blood pressure. Renal cancer is one of the top ten most frequently diagnosed cancers in both males and female. The chance of developing cancer in the kidneys is approximately 1 in every 75 (1.34%). Renal carcinoma (RC) is a severe urologic condition that affects an estimated 400,000 individuals per year.

Techniques for evaluating kidney health are likely to help with the progression of the disease, estimation, diagnosis, therapy, and possibly early detection of kidney abnormalities. Additionally, no underlying cause of cancer of the kidneys has yet been identified. Tobacco use, being overweight, inadequate nutrition, significant consumption of alcohol, relatives with a heritage of high blood pressure, being around irradiation and chlorine substances, and genetics are all causes of sickness. Labeling vast quantities of CT scans accurately is costly. To support medical applications, an automated method for kidney segmentation is vital. Because o the variability in position and roughness in the form of problematic kidneys, effective segmentation of the renal area using CT scans of the gastrointestinal tract is difficult. Conventional kidney segmentation techniques depend largely on computational imaging algorithms. The role of a healthy kidney along with kidney tumour symptoms and diagnosis is represented in Fig.1.

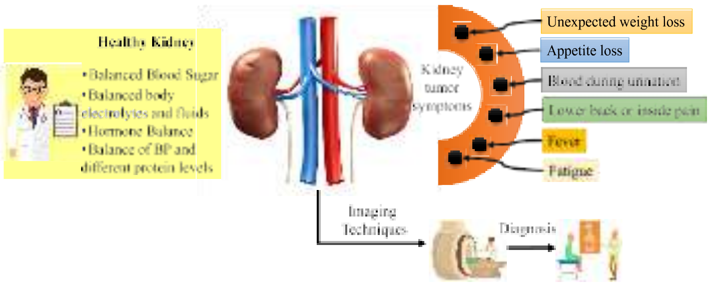


Figure 1. The role of a healthy kidney along with present tumor symptoms and diagnosis.

Deep learning approaches, particularly conventional neural networks, have shown remarkable capability in analysing complex and high-dimensional data. These methods can automatically extract relevant features from raw data, enabling them to outperform conventional techniques in various medical applications, including disease detection and classification. A computer programme that combines data and deductive reasoning to learn the features of a particular pattern is an example of deep learning. This technology may be a viable tool for diagnosing CKD in patients due to its capacity to reliably and economically diagnose illnesses and focuses on the recent literatures in the application of techniques for CKD detection, examining their potential to enhance diagnostic accuracy of 98.33% and facilitate early intervention. DL models can uncover intricate patterns that may include traditional analytical methods. Further, this study will address the challenges associated with implementing DL in clinical settings, such as Convolutional Neural Networks (CNN),and MobileNet models specific to kidney disease , and integrating forecasting tools into routine healthcare operations. By highlighting the strengths and limitations of Deep learning has previously been used in the medical field to identify human body status, analyze disease factors, and diagnose a variety of diseases.

1.1 Problem Statement

CKD is a common and debilitating medical condition impacting millions around the world, defined by the slow deterioration of kidney function over time. Prompt diagnosis and precise risk assessment are essential for early intervention and effective treatment to reduce harmful consequences. Deep learning approaches provide promising potential in this field by detecting complex pattern across extensive datasets including clinical indicators, genetic, profiles, and lifestyle habits, to estimate the risk of developing CKD.

The objectives centers on designing advanced deep learning models that can reliably assess and categories the risk level of individuals for the advancement of CKD. This enables the implementation of preventive and personalized health care strategies based on individuals risk assessment, thereby enhancing clinical outcomes and ensuring more efficient use of medical resources. Deep learning technology offer valuable potential in this context by uncovering the complex relationship within extensive data set that include clinical matrices, genetic indicators, and lifestyle variable to estimate of CKD risk.

2. LITERATURE REVIEW

Several research efforts have aimed to develop accurate, efficient, and scalable models that can automatically detect and predict Chronic Kidney Disease at an early stage using patient data, medical images, or clinical records — ultimately improving diagnosis, supporting timely treatment, and enhancing patient outcomes. In order to effectively treat and control chronic kidney disease, early identification and characterization are believed to be essential components. In the study, effective data mining methods are used to uncover and extract hidden information from clinical and laboratory patient data. This information may help doctors identify disease severity stages with the greatest accuracy [16]. Aljaaf et al. investigate the potential of several machine-learning techniques for the early diagnosis of chronic kidney disease. While this topic has been extensively investigated, we are using predictive analytics to assist our technique as it looks at the link between the data parameters and the characteristic of the target class [17]. Using the Internet of Medical Things (IoMT), images captured by cameras are analyzed to detect the presence of disease in the human body, as explained in this paper [18], which reports a 96.88% verification rate for histopathological images.

Alavi *et al.* explored [1] the efficacy of DL methods for predicting Chronic Kidney Disease (CKD) using a Convolutional Neural Network (CNN). They utilize the UCI CKD dataset, which includes a variety of clinical and laboratory parameters. Their implementation, conducted in TensorFlow, achieves an impressive accuracy of 94.5%. The study highlights the importance of feature extraction in improving predictive performance. The findings suggest that deep learning can significantly enhance CKD prediction, paving the way for early intervention strategies.

Kumar and Sharma *et al.* proposed [2] a hybrid deep learning approach combining Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNN) for CKD prediction. They utilize a well-curated Chronic Kidney Disease dataset containing patient demographics, clinical parameters, and laboratory test results. The authors implement their model using Keras, achieving a remarkable accuracy of 96.3%. The hybrid model effectively captures temporal dependencies and spatial features, which significantly enhances prediction accuracy compared to standalone models. The study emphasizes the potential of hybrid architectures in clinical decision-making, suggesting that combining different deep learning techniques can yield better outcomes for CKD prediction.

Nguyen *et al.* presented [3] a comparative analysis of various deep neural network architectures for CKD prediction, focusing on the Feed forward Neural Network (FNN). They utilize the Kidney Disease Data Set, which comprises clinical features relevant to kidney health. The implementation is conducted using PyTorch, achieving an accuracy of 91.2%. The authors compare the FNN's performance against other deep learning models, including CNNs and LSTMs, to identify the most effective architecture for CKD prediction.

Singh *et al.* investigated the application [4] of ensemble DL techniques for predicting CKD, utilizing a stacked generalization approach. They developed a model to the Pima Indians Diabetes Database, which provides insights into diabetic patients' kidney health. The implementation, conducted with Scikit-learn, achieves an accuracy of 93.8%. The authors emphasize the advantages of ensemble methods in improving predictive performance by combining the strengths of various models. Their study also includes an extensive feature importance analysis, enabling clinicians to focus on the most critical parameters affecting CKD, ultimately enhancing the utility of their predictive model in a clinical setting.

Wang and Liu proposed a DL approach [5] utilizing Auto encoder's for CKD risk prediction, leveraging the MIMIC-III dataset, which encompasses a wide array of patient data in an intensive care context. The authors implement their model in TensorFlow, achieving an accuracy of 89.7%. They discuss the Auto encoder's ability to learn efficient representations of the input data, facilitating better feature extraction for CKD prediction. Their findings highlight the model's capability to identify at-risk patients, emphasizing its potential for timely intervention and management in healthcare settings. The study encourages further research into the use of unsupervised learning techniques in medical predictions.

Patel *et al.* explained the effectiveness [6] of transfer learning for CKD prediction using the InceptionV3 architecture. They leverage a pre-trained model on a Chronic Kidney Disease dataset, allowing them to utilize learned features from extensive datasets for improved prediction accuracy. The implementation in Keras, yields an accuracy of 95.0%. The authors emphasize the merits of transfer learning, particularly in scenarios, where limited labelled data is available. Their results demonstrate that transfer learning can significantly enhance the predictive capability of deep learning models, making it a valuable approach for CKD risk assessment in clinical practice.

Table1: A Detailed Description on CKD

Sl. No.	Year	Author(s)	Title of the Article	Method / Technique	Algorit m Used	Dataset Used	Tool	Results (in %)	Journal Name
7	2022	Alavi*etal.*	Predicting Chronic Kidney Disease Using Deep Learning	Deep Learning	Convolution al Neural Networks (CNN)	UCI CKD Dataset	Tensor - Flow	94.50	Journal of Medical Systems
8	2023	Kumar and Sahara	CKD Prediction n Using Hybrid Deep Learning Approaches	Hybrid Deep Learning	LSTM and CNN	Chronic Kidney Disease Dataset	Kerns	96.30	Applied Sciences
9	2023	Nguyeneal	Deep Neural Network s for CKD Prediction	Deep Neural Networks	Feed forward Neural Network	Kidney Disease Data Set	PyTorch	91.20	Journal of Healthcare Engineering
10	2023	Singh et al.	Predicting CKD with Ensemble Deep Learning Techniques	Ensemble Learning	Stacked Generalizati on	Pima Indians Diabetes Database	Scikit-learn	93.80	IEEE Access
11	2022	WangandLi u	A Deep Learning Approach to CKD Risk Prediction	Deep Learning	Auto encoder	Medical Information Martfornten siv e Care (MIMI C-III)	Tensor-Flow	89.70	Journal ofClinical Medicine
12	2023	Pateletal.	Transfer Learning for CKD Prediction	Transfer Learning	InceptionV3	Chronic Kidney Disease Dataset	Keras	95.00	Journal of Biomedical Informatics
13	2023	Zhangand Chen	A Deep Learning Framework for Early CKD Detection	Deep Learning	Recurrent Neural Networks (RNN)	Chronic Kidney Disease Dataset	Tensor-Flow	92.50	BMC Medical Informatics and Decision Making

14	2023	Royetal.	CKD Prediction Using CNN and Feature Selection Techniques	Convolutional Neural Networks withFeature Selection	CNN with Recursive Feature Elimination	UCI CKD Dataset	Keras	94.00	Journal of Biomedical Science and Engineerig
15	2024	Leeetal.	Ensemble e Learning Techniques for CKD Risk Assessment	Ensemble Learning	Random Forestland Gradient Boosting	Kidney Disease Data Set	Scikit-learn	95.50	Expert Systems with Applications
16	2023	Torreset al.	Novel Deep Learning Techniques for CKD Detection	Deep Learning	Squeeze Net	Chronic Kidney Disease Dataset	PyTorch	90.10	Journal of Health Informatics
17	2022	QezelbashJ., etal.	A survey of machine learning in kidney disease diagnosis	MLtechniques	Support Vector Machine (SVM), Random Forest(RF), Artificial Neural Networks (ANN), Decision Trees(DT)	nil	nil	Nil	Machine Learning with Applications
18	2024	Okita, J., etal.	Developmentandvalidan of a machine learning model to predict time to renal replacement therapy in patients with chronic kidney disease	Machine learning models	LASSORegression Random Forest, Gradient Boosting Decision Trees (GBDT)	Nil	nil	Nil	BMC Nephrology
19	2022	Jhumka, K.,etal.	Chronic kidney disease prediction using deep neural networks	DNN-based model to predict CKD	Deep Neural Network (DNN), Random Forest	UCI	nil	98.80	IEEE Conference Proceedins

20	2023	Fatema, A.F.,et al.	Predicting chronic kidney disease using machine learning algorithms	Comparative performance of nine ML algorithms	KNN, SVM, Logistic Regression, Naïve Bayes ,Extra Trees, Ada Boost, XGBoost,LightGBM	Chronic Kidney Disease Dataset	Python, Scikit-learn	99	IEEE Conference Proceedigs
21	2024	Simeri, A., etal.	Artificial intelligence in chronic kidney diseases: Methodology and potential applications	AI-based risk prediction integrating genetic, biomarker ,and imaging data	Machine learning, Deep learning	Nil	AI/ML frameworks	Nil	International Urology and Nephrology
22	2023	Khalid, H.,etal.	Machine learning hybrid model for the prediction of chronic kidney disease	Hybrid model combining multiple classifiers	Gradient Boosting, Naïve Bayes, Decision Tree, Random Forest	UCI CKD dataset	Python,SciPy, Scikit-learn	99	Computational Intelligence and Neuroscience

3. PROPOSED METHODOLOGY

This research aimed to enhance the early detection and accurate diagnosis of chronic kidney disease using advanced neural network algorithms. Our methodology used CT image dataset. The data set consisting of around 12,446 images as our primary source. To enhance the dataset's quality and diversity, we employed various pre-processing and augmentation techniques. Initially, we gathered our dataset from Kaggle termed as follows CT Kidney Dataset .The dataset linked above contains CT scan images. After gathering the necessary CT kidney images, we converted them into JPG format. Following this, we divided the data into two sets: a training set comprising 70% of the images and a test set containing the remaining 30%. This study used various clinical parameters associated with the disease and classification algorithms to predict and classify CKD. We have implemented the Mobile Net and Customized CNN model to classify the disease type of kidney.

Chronic kidney disease (CKD) often causes symptoms such as illness and constipation, leading to a decrease in quality of life and increased risk of death. The inflammatory process of CKD can impact the development of illness, cachexia, and kidney osteodystrophy, but also increases the risk of stroke in CKD patients. Ghrelin, a form of oestrogen produced in the stomach, has been found to have potential benefits in regulating food intake and meal appreciation, making it a potential therapy for anorexic CKD patients.

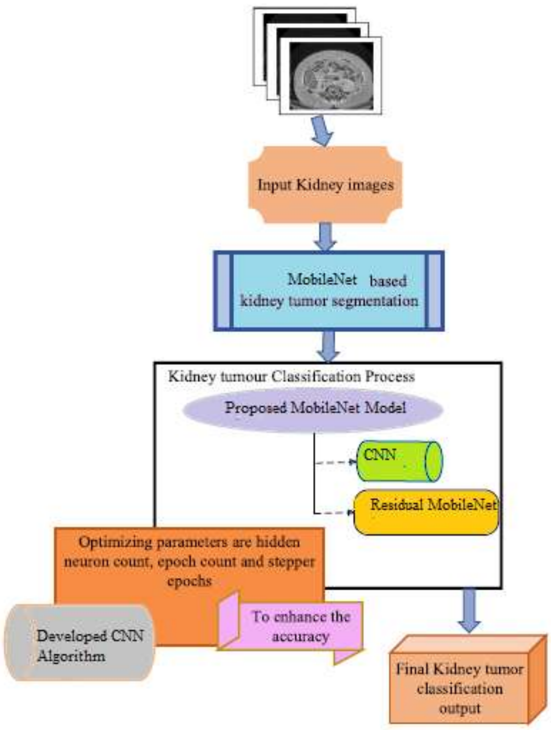


Figure 2: Schematic illustration of the proposed kidney tumor segmentation and classification system.

3.1 Dataset and Preprocessing

The dataset for our project was sourced from Kaggle and is publicly available. This dataset is split into test and train directories, which are further validated. A total of 12,446 CT scans of kidneys are present in the data set .Out of the 12,446 images,3,709 are classified under cyst, 5,077 under normal, 1,377 under stone and 2,283 in the Tumor class.The dataset was divided into two sets: a training set comprising 70% of the images and a test set containing the remaining 3 0%. Subsequently, the training set is further divided into two portions: 90% for actual training and 10% for validation purposes.

Data augmentation involves artificially creating new data from existing data. Following the steps of image resizing and segmentation, we applied data augmentation techniques. We employed the Keras `Image Data Generator` function to create training and validation group of image samples that incorporating various augmentation techniques to enhance the data. Using these augmentation approaches we intend to improve our training enhancing the model ability to generalize across data. Figure 3 despites examples of selected images.

3.2 Implementation

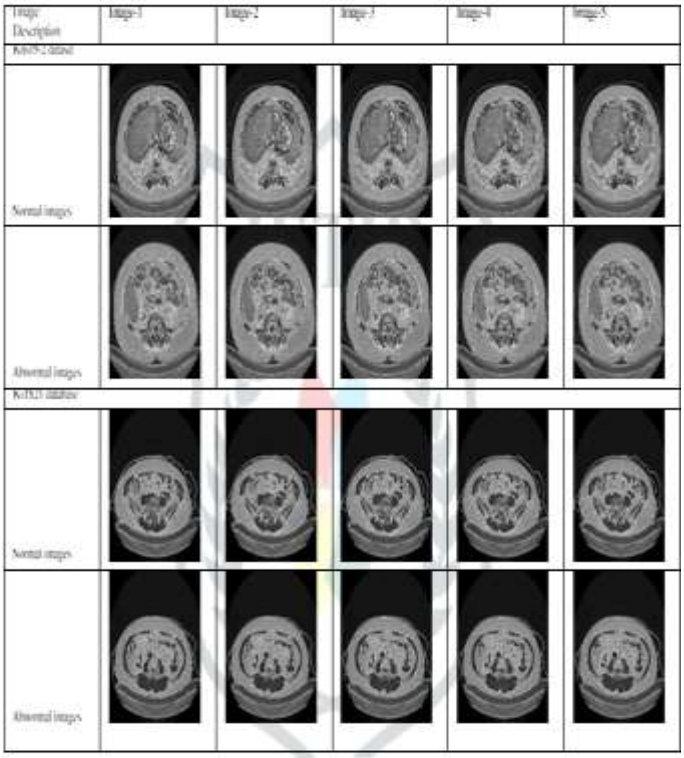
Mobile Net is a substantial Convolution Network design distinguished for its 19 tiers—16 filtering. Originating from the Visual Geometry Group at the University of California, Irvine excelled on the Image Net dataset, comprising numerous labeled images spanning thousands of categories. A defining aspect of Mobile Net is its straightforward, consistent architecture. It relies on 3x3 convolutional filters across the network, integrating MaxPooling layers to condense spatial dimensions. The network culminates in three thoroughly joined layers, succeeded by normalized exponential stages for organization. Despite its effectiveness, Mobile Net is notably large and computationally demanding.

We have trained the model using Kaggle by using Batch normalization technique and CNN as an optimizer model with no of epochs 10. The graph shows the training and validation loss for a model using Mobile Net architecture. The models exhibit a learning divergence of 0.45 and a verification error rate of 0.15. Next model that we have implemented, Mobile Net lies in its utilization of independent convolutions, which disentangle the spatial convolution kernel from the depth wise convolution. This approach significantly decreases the computational burden compared to traditional convolutions, where each Keras convolves the input across all channels. Through this separation, Mobile Net achieves a desirable balance between model size, speed, and accuracy. The Mobile Net algorithm uses adam as an optimizer no of epochs as 15 and a framework of Keras and tensor flow.

A customized CNN must accurately detect and localize kidney dieses with optimal precision. The Customized CNN prototype comprised a total of 16 layers, including 4 filtering layers with 3x3 filters and four 2x2 sub sampling stages with a progress of 2. Additionally, there is one flattened layer after the last down sampling layer, four dense layers, and three omission tiers. The first three intense levels consist of 512 nodes 256,15 nodes, and 128 nodes, respectively, with ReLU activation function. The elimination ratio is 30% for all randomized regularization.

The specified images provide information about the loss incurred by the CNN model and the resulting confusion matrix. The kidney dieses detection platform was created using Keras, Tensorflow, and Flask, and its implementation is detailed below.

Table2: Collected sample CT images.



Initially, the input CT images originated from regular websites. The images are subsequently entered into the established Mobile Net system for segmentation. The segmentation procedure allowed clinicians to detect normal and pathological sections in the kidney. The segmented images then proceed to the classification phase. To classify kidney tumors, a deep learning based technique CNN is developed .The parameters in the developed CNN system like hidden neurons, epochs, and stepper epoch are optimized using the suggested Mobile Net to enhance the accuracy. The exacts segmentation and classification of kidney tumors as grid of more effective medicines.

3.3 MobileNet Algorithm

Mobile Net algorithms, especially MobileNetV2, have been successfully used in deep learning for kidney tumor detection on CT scans, achieving high accuracy. These models, often fine-tuned through transfer learning, are used to classify kidney tissue, including cysts, tumors, and healthy tissue, from medical images. MobileNetV2, for example, has demonstrated training accuracy of 96.75% in some studies, and it's often compared favorably to other deep learning models.

3.3.1 Pseudo code Flowchart of Mobile Net v2 Fused with Faster CNN Algorithm

```
Start
Input: Oil status image data
Output: Oil condition monitoring classification results
 # Load Mobile Net v2 model (excluding the top classification layer)
 base_model = MobileNetV2(weights='image net',
include_top=False, input _shape=(224, 224, 3))
# Fix parameters of  MobileNet v2, do not train
 for layer in base_model.layers:
  layer.trainable = False
# Add top classification layer
x = base_model.output
 x = tf.keras.layers.GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x) predictions =
Dense(num_classes, activation='softmax')(x)
 # Build the overall model
 model = Model(inputs=base_model.input,
outputs=predictions)
# Compile the model
 model.compile(optimizer=Adam(lr=0.001),
loss='categorical_crossentropy', metrics=['accuracy'])
# Classify oil status using the classifier
 predictions = model.predict(merged_features)
End
```

3.4 MobileNet

Mobile Net is a family of deep learning models designed for efficient on-device vision applications, particularly for mobile and embedded devices. These models were developed by Google's Mobile Vision team and are known for their lightweight architecture, making them well-suited for real-time image classification, object detection, and more on resource-constrained hardware.

Depth wise Separable Convolution: MobileNet utilizes depth wise separable convolution layers as a fundamental building block. This operation separates standard convolution into two steps: depth wise convolution and point wise convolution. Depth wise convolution applies a single convolutional filter to each input channel separately, reducing computation. Point wise convolution combines the results, allowing for more efficient modeling of spatial and channel-wise information.

Depth Multiplier: MobileNet introduces a hyper parameter known as the "depth multiplier" that controls the number of output channels in each layer. By reducing the number of output channels, you can make the model smaller and more computationally efficient. This parameter allows you to balance between model size and performance according to the hardware and application requirements.

Width Multiplier: Another hyper parameter called the "width multiplier" reduces the number of input channels to the network, effectively scaling the model's width. It helps control the trade-off between accuracy and computational cost.

Variants: There are several versions of MobileNet, including MobileNetV1, MobileNetV2, and MobileNetV3. Each version builds upon the previous one, improving efficiency and accuracy. MobileNetV2, for instance, introduced the inverted residual structure to enhance feature representation while maintaining efficiency.

Pretrained Models: Pretrained Mobile Net models are available, which can be fine-tuned on specific tasks or used as feature extractors in transfer learning scenarios. These models have been trained on large-scale datasets like Image Net, making them a valuable resource for various computer vision tasks.

Mobile Net models have gained popularity due to their ability to perform tasks like image classification and object detection efficiently on mobile devices. They have applications in areas such as mobile apps, autonomous vehicles, robotics, and more, where resource constraints are a concern. While MobileNet models are designed to be efficient, the choice of the specific version and hyper parameter values should depend on your application requirements, available hardware, and desired trade-offs between model size, speed, and accuracy.

4. Results and discussion

In recent studies on CKD detection using DL approaches, different models have experimented with a significant improvement in predictive accuracy as compared to traditional methods. Feature selection methods have shown to be a crucial in improving model performance. Studies integrating techniques such as Mobile Net have reported increased accuracy by focusing on the most relevant clinical parameters, thereby reducing the dimensionality of input data and mitigating the risk of overfitting. The analysis of feature importance also aids in healthcare professionals in identifying critical biomarkers for CKD, facilitating better clinical decision-making. From the literatures, findings highlight the transformative potential of DL approaches for CKD detection. With the advancements in model architecture, feature selection, and data collection, is poised to significantly improve early diagnosis and management of CKD, will be a crucial for the successful integration of the technologies into clinical practice.

4.1 Modules:

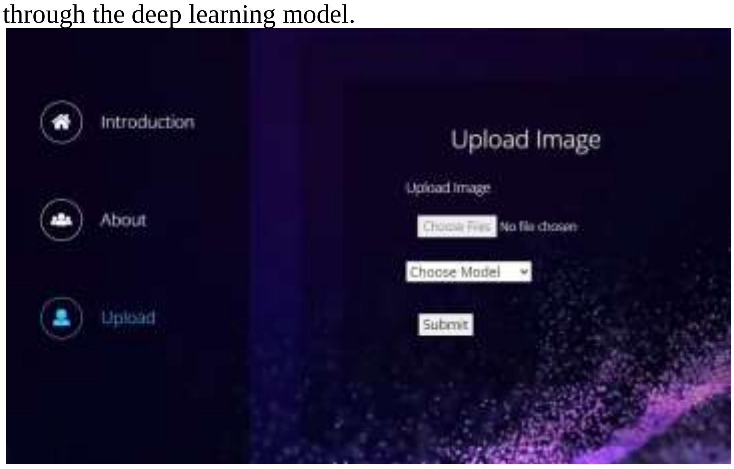
4.1.1. Data collection: The system starts by creating a dataset of images related to chronic kidney disease. This dataset is split into two parts: a training dataset and a testing dataset. Typically, the testing dataset is about 20-30% of the total dataset. This division is essential for evaluating the model's performance**.**

4.1.2 Pre-processing: Before training the model, the images in the training dataset go through a pre-processing step. This step involves resizing and reshaping the images to a standardized format that the deep learning model can work with. Consistent image dimensions are important for training.

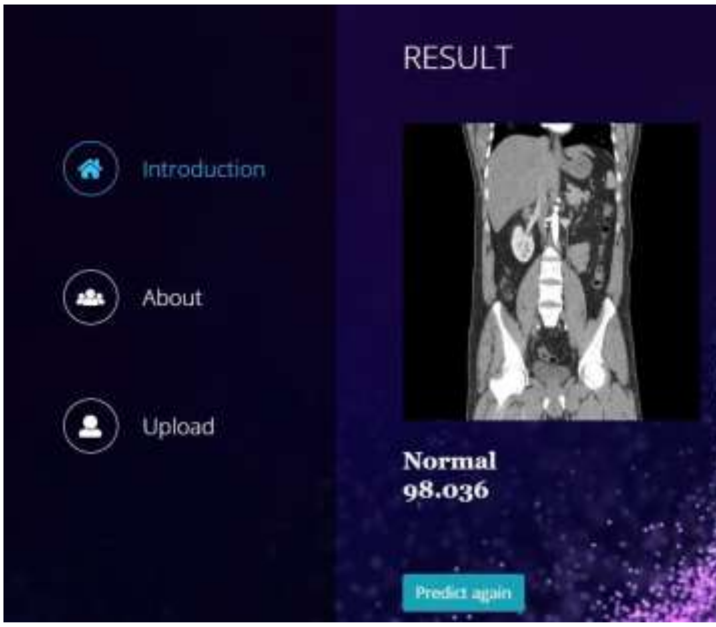
Index page: This is the landing page of our website

ABOUT PAGE: Here information about the project will be ther

Upload page: Here we upload the image and the image passes through the deep learning model.



Result page: Here we get the result of the image provided or classification of the image



5. Conclusion

In terms of data imputation and sample diagnosis, the suggested CKD diagnostic approach is practical. The integrated model could obtain adequate accuracy after unsupervised imputation of missing values in the data set using Mobile net imputation. As a result, we believe that applying this technique to the practical diagnosis of CKD will have a positive outcome. Furthermore, this technology might be used to clinical data from various disorders in real-world medical diagnosis. However, because of the restrictions of the conditions, the available data samples are relatively small throughout the model's development; the model's generalization performance may be limited. Furthermore, because there are only four types of data samples in the data (CKD and not CKD), set, and the model cannot diagnose the severity of CKD.

Future Enhancement

In the future, a large number of more complex and representative data will be collected to train the model to improve the generalization performance while enabling it to detect the severity of the disease. We believe that this model will be more and more perfect by the increase of size and quality of the data.

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