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Normal Cyst- Tumor and Stone Detection by Using Machine Learning and Deep Learning

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ABSTRACT
Renal diseases present a major global health issue, making it essential to have accurate diagnostic tools to enhance patient outcomes. This research focuses on this necessity by examining three primary types of kidney diseases: stones, cysts, and tumours. Deep Learning (DL) detection algorithms have the potential to enhance testing accuracy while decreasing diagnostic times, the workload for radiologists, and overall costs. The study introduces Computational Intelligence with a Deep Learning Decision Support System for Kidney Cancer (CIDLDSSKC) methodology applied to renal imaging. Timely diagnosis can greatly improve the chances of a favorable prognosis for patients. Creating an artificial intelligence-driven system to aid in the diagnosis of kidney cancer is vital, as kidney-related ailments are a worldwide health issue, compounded by the scarcity of qualified nephrologists to assess kidney cancer.
Identifying and classifying various types of renal failure poses the greatest challenge in treating kidney cancer. Renal Cell Carcinoma (RCC), which constitutes about 85% of adult kidney cancer cases, presents substantial diagnostic difficulties. Timely detection is vital for successful prevention and treatment; however, the manual evaluation of whole slide images (WSI) is labour-intensive and susceptible to inconsistencies. To tackle these challenges, we propose a Computational Intelligence with Deep Learning-Based Decision Support System for Kidney Cancer (CIDLDSSKC). Renal Cell Carcinoma (RCC), which makes up roughly 85% of adult cases, presents significant diagnostic obstacles. Early identification is essential for effective prevention and treatment, but the manual analysis of whole slide images (WSI) remains tedious and vulnerable to variability.

Keywords: Acute Kidney Disease, Chronic Kidney Disease, Machine Learning, Python Programming, Deep Learning.

1. INTRODUCTION

The initiative seeks to create a diagnostic system powered by AI that employs Machine Learning (ML) and Deep Learning (DL) approaches for the prompt identification, evaluation, and categorization of three primary kidney conditions: kidney stones, cysts, and tumors, with a particular emphasis on Kidney Cancer, notably Renal Cell Carcinoma (RCC), which represents roughly 85% of all kidney cancer instances. This system will utilize cutting-edge medical imaging methods such as CT scans, MRIs, and ultrasounds to examine renal images and detect critical abnormalities, such as the existence of stones, cysts, and possible malignant tumours. Through the Prof. Ratnamala Paswan Dept. of Computer Engineering of Pune Institute of Computer Technology Pune, India rspaswan@pict.edu application of Deep Learning algorithms (e.g., Convolutional Neural Networks), the project aims to streamline the detection and classification processes, greatly enhancing diagnostic precision and lessening the burden on healthcare professionals, including radiologists and nephrologists. Focusing on the importance of early detection, the system aims to identify not only prevalent kidney ailments but also the initial indicators of kidney cancer, promoting prompt intervention and enhancing patient outcomes. The Computational Intelligence with Deep Learning Decision Support System for Kidney Cancer (CIDLDSSKC) will be developed to aid healthcare professionals by highlighting questionable findings in medical imaging, thereby supporting improved decision-making. This AI-based method will address the difficulties associated with manual image analysis, which can be labour-intensive and susceptible to human mistakes, by offering a uniform and dependable resource for diagnosing kidney conditions. In the end, the project seeks to enhance the creation of an affordable, easily available, and extremely precise decision support system that can aid in the prompt identification and diagnosis of kidney cancer and other renal issues, thereby enhancing the efficiency and quality of patient care.

2. MOTIVATION

The motivation behind developing a machine learning and deep learning system for kidney disease detection stems from the growing global burden of kidney-related disorders, such as cysts, kidney stones. The motivation behind the study "Normal-Cyst Tumour and Stone Detection by Using ML & Deep Learning" stems from the pressing need to improve the accuracy and efficiency of medical diagnoses. While effective, traditional diagnostic methods are often time-consuming and reliant on the subjective judgment of medical professionals, which can lead to variability in outcomes. Misdiagnosis or delayed diagnosis of conditions like tumors and stones can have severe consequences, impacting patient survival rates and quality of life. By applying machine learning and deep learning techniques to automate the detection and classification process, there is potential to standardize and expedite diagnoses, reduce human error, and allow healthcare providers to focus appropriate style is still applied to each section, reapplying styles if necessary.

3. LITERATURE SURVEY

A thorough summary of all the collected research articles has been provided. Recent advancements in machine learning (ML) and deep learning (DL) have significantly enhanced the accuracy and efficiency of medical image analysis, particularly in the detection and classification of normal cysts and tumors.

3.1 KEY TAKEAWAYS FROM THE STUDY

- **a)** Growing Role of AI in Kidney Diagnosis Machine learning (ML) and deep learning (DL) are increasingly being explored to assist in the diagnosis of kidney conditions, especially to overcome the limitations of many methods, such as human error, time consumption, and inter observer variability.
- **b)** Need for Automated Multi-Class Classification Most studies focus on binary classification (e.g., cyst vs tumour), but there is a significant need for systems that can handle multi-class classification involving normal tissue, cysts, stones, and tumours (especially RCC).
- **c)** Imaging Modality Matters Most studies focus on CT or ultrasound images, but results vary significantly depending on the quality and type of imaging used.

3.2 SURVEY

- **Atherosclerotic Renovascular Disease:** A KIDGO (kidney disease: Improving Global Outcomes) Controversies & Conference- Evolving criteria for identifying kidneys with salvageable function in renal artery stenosis. Certain high-risk populations with specific clinical manifestations may benefit from revascularisation.

- **Machine Learning–Aided Chronic Kidney Disease Diagnosis Based on Ultrasound Imaging Integrated with Computer-Extracted Measurable Features-** The model aided by automated machine learning, performed well in segmenting, measuring, and classifying kidney ultrasound images.
- **A deep learning-based precision volume calculation approach for kidney and tumour segmentation on computed tomography images-** Absence of comparison with existing state-of-the-art methods for kidney and tumour segmentation on CT images. Nephrogenic Systemic Fibrosis in Patients with Chronic Kidney Disease after the Use of Gadolinium-Based Contrast Agents- Contact clinicians to understand the clinical characteristics and risk factors of NSF to prevent and recognise the condition effectively.
- **Clinical Decision Support System Based on Hybrid Knowledge Modelling: A Case Study of Chronic Kidney Disease-Mineral and Bone Disorder Treatment-** Achievement of high service reliability and dependability coefficients with the proposed CDSS.
- **Harmonising acute and chronic kidney disease definition and classification: report of a kidney disease: Improving Global Outcomes (KDIGO) Consensus Conference**- Proposal of a prediction framework for CKD based on various classifiers.
- **Chronic kidney disease prediction based on machine learning algorithms-** Proposal of a prediction framework for CKD based on various classifiers.
- **A Case Study of Chronic Kidney Disease-Mineral and Bone Disorder Treatment-** Development of a clinical decision support system (CDSS) tailored for clinicians managing chronic kidney disease.
- **A Deep Learning Approach for Kidney Disease Recognition and Prediction through Image Processing-** Deep learning in medical imaging offers precise management for kidney diseases, aiding in organ segmentation.
- **Chronic kidney disease correlates with MRI findings of cerebral small vessel disease-** Creation of a web-based application serving as a "self-diagnostic" tool for medical practitioners to aid in CKD diagnosis.
- **Chronic Kidney Disease Prediction using Machine Learning Models** – Machine learning models utilizing ensemble algorithms offer an effective means of predicting chronic kidney disease at an early stage.
- **Machine learning in the detection of dental cyst, tumor, and abscess lesions-** The paper focuses on evaluating and comparing the effectiveness of different texture analysis techniques— GLCM, GLRLM, and wavelet analysis—in detecting and classifying dental cysts, tumours, and abscesses from panoramic radiographs using machine learning, specifically a Support Vector Machine (SVM) classifier.
- **Deep learning-based diagnosis for cysts and tumours of the jaw with massive healthy samples- two-branch neural network is proposed—first pretrained on healthy images, then fine-tuned to classify lesions and segment affected areas.**
- **Multiple Cancer Types Classified Using CTMRI images based on learning without forgetting, powered deep learning models-** The paper aims to classify multiple cancer types (lung, brain, breast, cervical) using CT and MRI images through deep learning models enhanced by Learning without Forgetting (Lwf). By using various CNN architectures with transfer learning and Bayesian optimisation, the study achieves high accuracy, especially with MobileNet V3. It also proposes a user-

friendly Flask interface for real-world testing, highlighting AI's potential in early and accurate cancer diagnosis.

- **Deep Learning Model-Based Decision Support System for Kidney Cancer on Renal Images-** The system combines image preprocessing, feature extraction with Exception, and classification via β Variational Autoencoder, optimised using the Flower Pollination Algorithm.

4. PROBLEM STATEMENT

Kidney diseases, with conditions like kidney stones, cysts, and tumours, pose a major global health problem, where kidney cancer, primarily Renal Cell Carcinoma (RCC), is a leading cause of morbidity and mortality. Timely diagnoses of these diseases are critical for optimising patient outcomes, but existing diagnostic processes — mainly based on visual interpretation of medical images — are time-consuming, human error-prone and sensitive to inter-observer variability. The biggest hurdle is building an AI-based decision support framework capable of effectively.

5. SCOPE

- **Data Collection & Preparation:** The images will come from normal kidney tissue as well as samples labelled with kidney stones, cysts, and tumours. This dataset not only has that information but also RCC types to use this data to train the selected algorithm to discriminate between benign and malignant growths.
- **Data Collection & Preparation:** The dataset will contain labelled images of normal kidney tissue, as well as infected/some pathology images with kidney stones/cysts/tumors, etc. It will also have images of different stages of Renal Cell Carcinoma (RCC) for the model to learn to differentiate between benign and malignant growths.
- **Data Learning Model Development:** The model will be trained using a supervised learning approach, utilising labelled data to recognise patterns in kidney images indicative of different diseases.
- **Preprocessing of Medical Imaging Data:** Additionally, segmentation techniques will be employed to identify and isolate the kidney regions from the background, improving the focus on structures of interest, such as tumours or stones. The scope of this project encompasses the entire workflow of AI-assisted kidney disease detection, from data collection and model training to system deployment and clinical validation, with a primary focus on improving the early detection of kidney cancer (RCC). The outcome will be an efficient, accurate, and cost-effective diagnostic tool that can aid healthcare professionals in providing timely and precise care.

6. SOFTWARE REQUIREMENT SPECIFICATIONS

a) Purpose & scope of the document: The purpose of this Software Requirement Specification (SRS) document is to outline and define the software requirements for the Kidney Disease Detection System. This system utilises Machine Learning (ML) and Deep Learning (DL) algorithms to detect and classify various kidney diseases, including kidney stones, cysts, tumours, and specifically Renal Cell Carcinoma (RCC). This document serves as a comprehensive reference for the development, testing, and deployment of the system. It provides stakeholders, including developers, 4 healthcare professionals, and system administrators, with a clear understanding of the system's functionality.

b) Usage Scenario: The Kidney Disease Detection System utilises Machine Learning (ML) and Deep Learning (DL) algorithms to aid healthcare professionals in diagnosing kidney related diseases, including kidney stones, cysts, tumours, and specifically Renal Cell Carcinoma (RCC).

c) Detecting kidney disease from medical imaging: Actors- User: Radiologist or Clinician (Healthcare Professional) Secondary User: System (kidney disease detection system).

Preconditions: The user (radiologist) has access to the Kidney Disease Detection System.

Flow of events:

Step 1- Once preprocessing is complete, the system uses a convolutional neural network model to analyse images. Step 2: The system displays the UI with an option to upload patient medical images. Step 3-The radiologist uploads a medical image by either dragging and dropping the image file or selecting it from their computer.

d) Disease Detection:

Step 1: Once preprocessing is complete, the system uses a convolutional neural network model to analyse images.

Step 2: Model identifies any abnormalities within the kidney region.

7. DETAILED DESIGN DOCUMENT

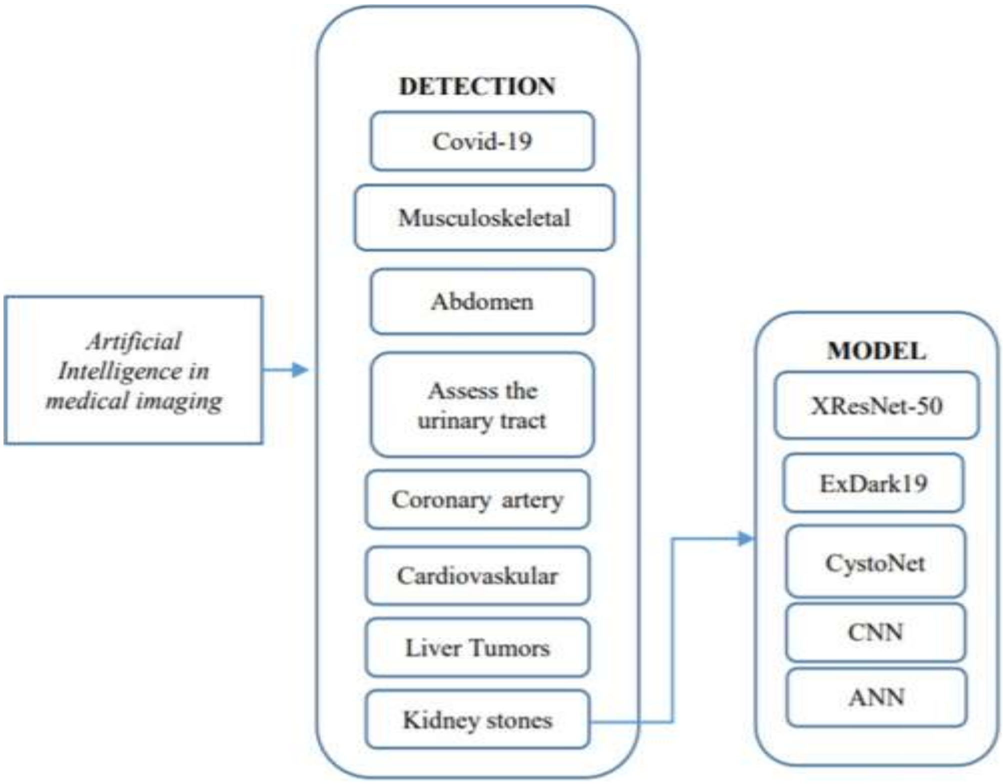

Figure 1.1 Design flow

7.1. EXPLANATION

- The proposed approach is comprised of three major operations, i.e., case–base partitioning, case selection, and case adaptation.
- The major emphasis of the proposed approaches to synthesize domain cases to generate a comprehensive recommendation for a complex scenario.
- The main contribution of the study is a proposed hybrid methodology that combines both explicit knowledge (i.e, acquired from domain experts in the form of a partial domain model) and implicit knowledge (i.e.. the Form of clinical cases) for complex multi-factor recommendations.

7.2. TOOLS & TECHNOLOGIES

i) Python -Django:

Django is a framework built in Python. We used Django for backend development. It is efficient in handling API requests and managing the database. Django provide various built-in functionalities, hence it is convenient to use Django for the backend.

ii) Generative AI:

Generative AI refers to machine learning models that create new content, such as text, images, or code, based on the patterns and structures they learn from existing data. These models are designed to simulate creativity and often produce outputs that are indistinguishable from human-generated content. In this project, generative AI models, particularly large language models (LLMs), play a critical role in interpreting user input in natural language and automatically generating code for data vi- visualisations. These visualisations, such as charts and graphs, are then created based on the dataset provided by the user. The goal is to enable users to interact with data through simple natural language prompts, bridging the gap between human language and complex data analysis.

iii) Deep Learning in CKD:

Deep learning, a subset of Machine Learning (ML), is a powerful tool that has shown great promise in automating the analysis of complex medical data such as medical images and clinical biomarkers. By leveraging large datasets and high-performing neural networks, deep learning algorithms can assist in diagnosing CKD at an early stage, monitor its progression, and predict future complications or the onset of End-Stage Renal Disease (ESRD). Deep learning techniques are particularly useful in CKD because of their ability to: 1.Analyse complex medical images (e.g., kidney ultrasounds, CT scans, MRIs). 2.Process patient data (e.g., blood tests, urine tests, and clinical records).

iv) Machine Learning in CKD:

Machine Learning (ML) has emerged as a powerful tool in the diagnosis, prognosis, and management of kidney diseases such as chronic kidney disease (CKD), kidney stones, cysts, tumours, and specifically Renal Cell Carcinoma (RCC). By utilising algorithms that can learn from large datasets, ML can help healthcare professionals in detecting kidney diseases more accurately, predicting disease progression, and providing personalised treatment recommendations. Machine Learning plays a crucial role in the detection, diagnosis, prognosis, and management of kidney diseases, including chronic kidney disease (CKD), kidney stones, cysts, and Renal Cell Carcinoma (RCC). By enabling early diagnosis, risk prediction, and personalised treatment recommendations, ML has the potential to revolutionise kidney care and significantly improve patient outcomes.

v) Data Pre-Processing (Pandas):

Pandas is a powerful Python library that is widely used for data manipulation and analysis. It offers data structures like DataFrames, which make it easy to load, clean, and preprocess data before analysis. In this project, Pandas is utilised to prepare and process the datasets uploaded by users. This includes tasks such as handling missing or invalid data, converting data types, filtering outliers, and ensuring that the data is in the correct format for generating visualisations.

7.3. MODELS USED

i) VGG –

We are using VGG16's convolutional base as a feature extractor, adding a custom classifier on top. This is a powerful method when you have a smaller dataset and don't want to train a huge model from scratch.

It is a typical deep Convolutional Neural Network (CNN) design with numerous layers, and the abbreviation VGG stands for Visual Geometry Group. The term "deep" describes the number of layers, with VGG-16 or VGG-19 having 16 or 19 convolutional layers, respectively. VGG is a classical convolutional neural network architecture. It was based on an analysis of how to increase the depth of such networks. The network utilizes small 3 x 3 filters. Otherwise, the network is characterized by its simplicity: the only other components being pooling layers and a fully connected layer.

ii) MOBILENET-

It builds an image classification model using transfer learning with a pre-trained MobileNetV2 architecture. It starts by loading MobileNetV2 without its top classification layers and uses input images of size 224x224 with 3 colour channels. To customise the model further, the last eight layers of the pre-trained MobileNetV2 are removed, and all remaining layers are set to be trainable, enabling fine-tuning during training. A new classification head is then added on top of the modified base. The accuracy metric is used to evaluate model performance during training and testing. Overall, the code prepares a lightweight yet powerful model tailored for a four-class image classification task.

iii) ResNET-

It constructs and trains an image classification model using ResNet50 as the base through transfer learning. It begins by importing necessary modules from TensorFlow and loading the ResNet50 model with pre-trained ImageNet weights, excluding its top classification layers. All layers of the ResNet50 base are set to be trainable, allowing full fine-tuning during training. A GlobalAveragePooling2D layer is added to reduce the feature maps to a vector, followed by a Dense layer with 512 units and Relu activation, regularised with L2 to prevent overfitting. A Dropout layer with a 50% rate is included to further reduce overfitting. The output layer is a Dense layer with several units equal to the number of target classes and a SoftMax activation for multi-class classification. The model is compiled using the Adam optimiser and sparse categorical cross-entropy loss, appropriate for integer- labelled data. This setup leverages the power of ResNet50 while adapting it to a new classification task.

8. RESULTS

This snippet displays a batch of 16 training images from a dataset using a 4x4 grid layout with Matplotlib. It retrieves the images and their corresponding labels using a data iterator, then visualizes each image with its label as the title. This helps verify that the images and labels are correctly paired and loaded, which is crucial before training a machine learning model, especially for tasks like image classification in medical diagnostics.

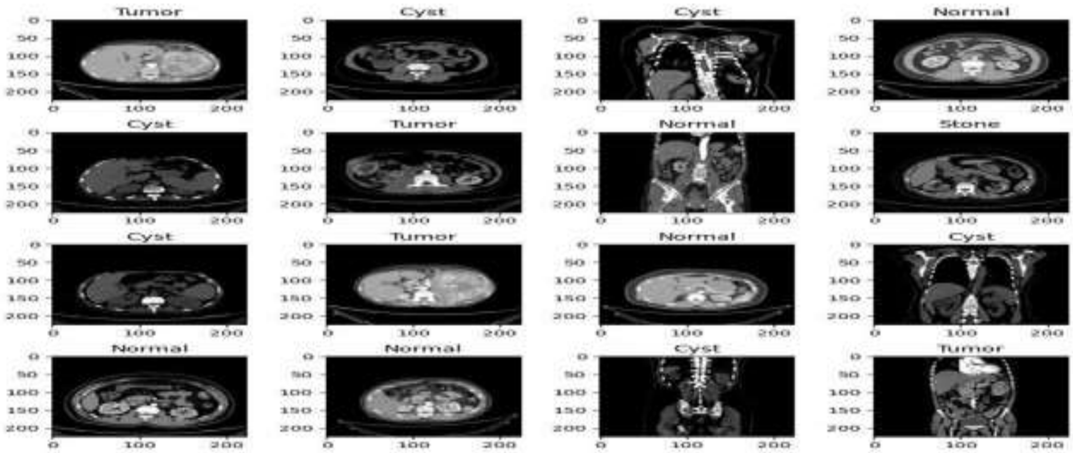

Fig 5. Training Images

8.1.Confusion Matrix:

The following graph visualises using the Confusion Matrix Display from scikit-learn. It illustrates the model's performance across four classes: Cyst, Normal, Stone, and Tumour, aiding in the assessment of its classification capabilities in each category.

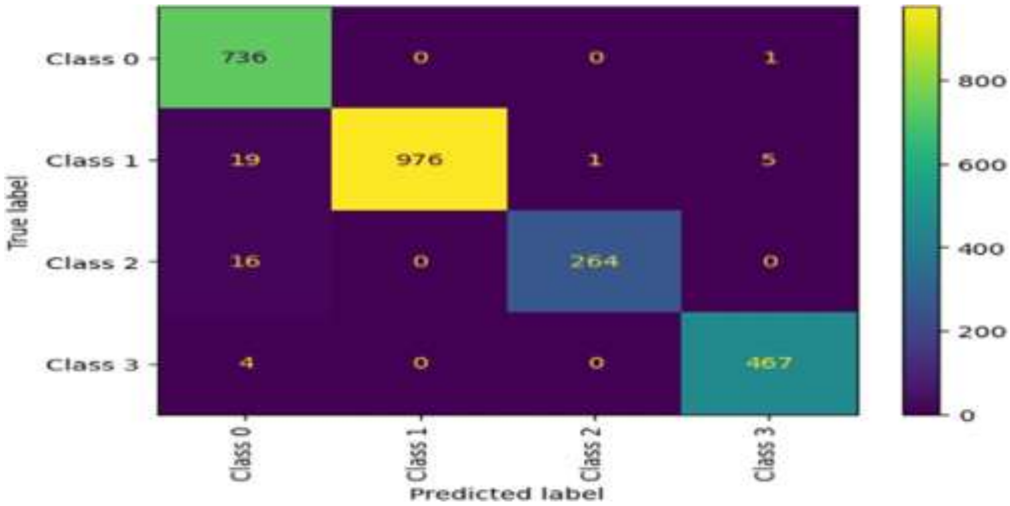

Fig: Confusion Matrix

8.2.CT- image of a kidney:

The following demonstrates a kidney CT image, resizes it to fit the input shape of a pre-trained Mobile Net model, and performs a prediction. It then identifies the most likely class label for the image using the output probabilities from the model.

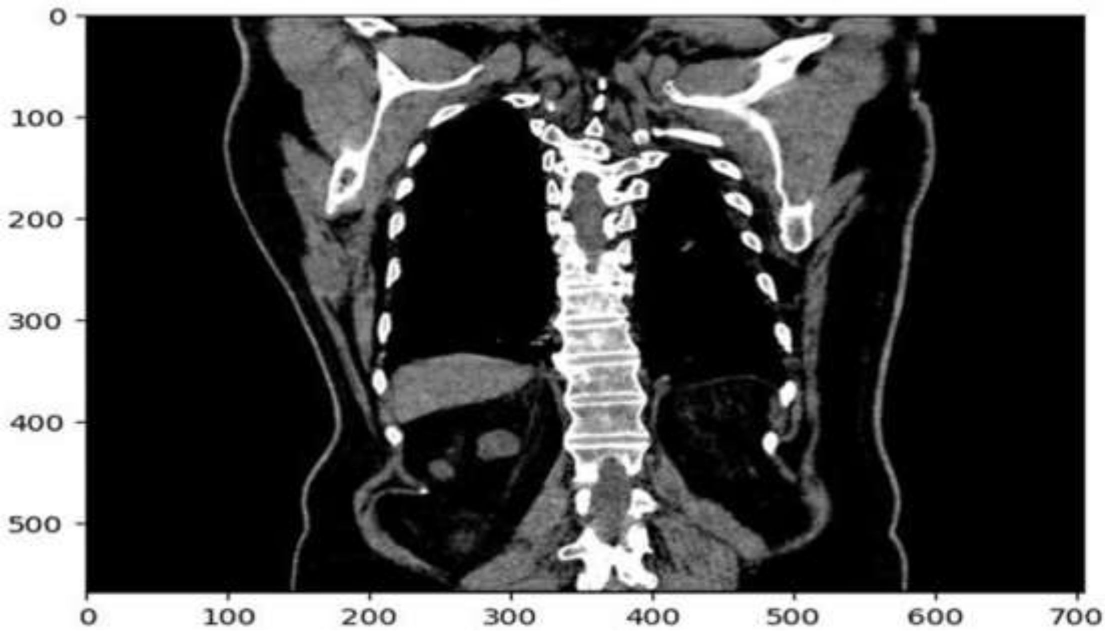

Fig: CT image of a kidney

8.3.Training & Validation Accuracy:

The chart illustrates the training and validation accuracy throughout all training epochs, allowing us to visualise how the model's performance enhances over time.

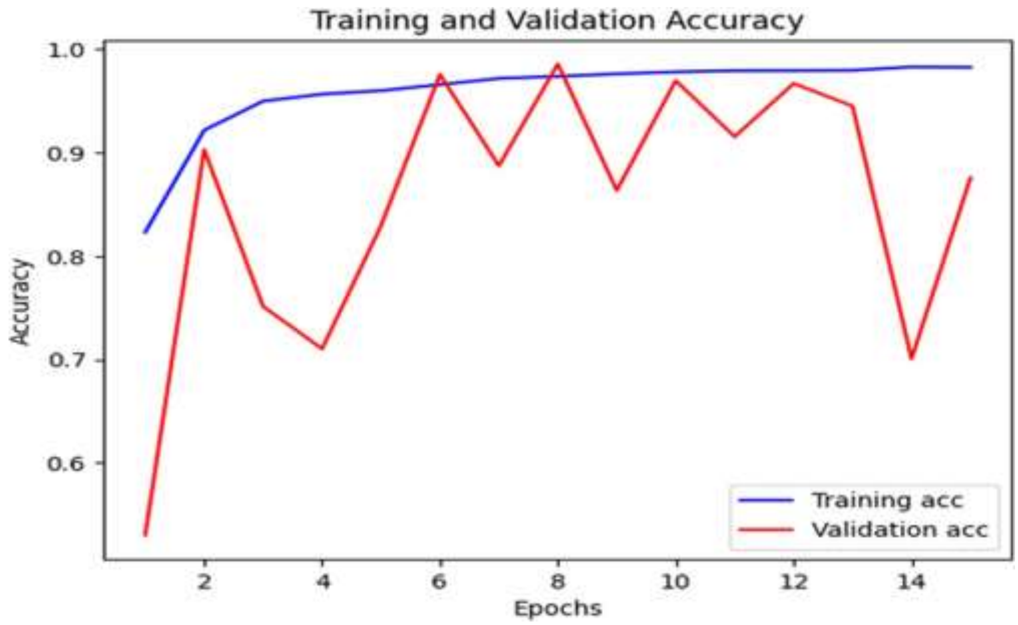

Fig: Final Training & Validation Accuracy

9. FUTURE SCOPE

The future potential of machine learning (ML) in the detection, diagnosis, and management of kidney diseases—including chronic kidney disease (CKD), kidney stones, cysts, tumors, and specifically Renal Cell Carcinoma (RCC)—is incredibly promising. As the healthcare industry increasingly adopts artificial intelligence (AI) and ML technologies, these tools are set to enhance both the accuracy and speed of kidney disease diagnoses, ultimately Improving patient outcomes through personalized treatment strategies. In the future, deep learning algorithms are anticipated to become more sophisticated, enabling them to identify complex patterns within large and diverse datasets. This development will lead to earlier and more accurate diagnoses. These algorithms will also advance in their ability to manage multimodal data, integrating clinical tests, medical imaging, genetic information, and patient histories to provide a comprehensive view of kidney health.

The growing availability of electronic health records (EHRs) and wearable health devices will enable real-time data streams, further empowering ML systems to predict acute kidney injury (AKI), monitor disease progression, and suggest timely interventions. By integrating multimodal machine learning models that combine clinical data, genomic data, and imaging, we can enhance the prediction of individual patient outcomes, such as the likelihood of CKD progression, the risk of developing End-Stage Renal Disease (ESRD), and the potential for complications like cardiovascular diseases or diabetes. With ongoing advancements in genetic research and the increasing availability of genomic data, ML models will be able to identify genetic markers linked to kidney disease susceptibility. This capability will pave the way for precision medicine, where treatment regimens are tailored to an individual's genetic profile, lifestyle, and environmental factors. In clinical applications, ML algorithms will be incorporated into clinical decision support systems (CDSS), offering real-time, data-driven insights that assist healthcare providers in making improved decisions about diagnosis treatment planning, and patient management. These systems will alleviate the workload of radiologists, nephrologists, and clinicians by automating the analysis of medical images (such as CT scans, MRIs, and ultrasounds) and clinical data, thereby ensuring more efficient workflows. Additionally, AI-based tools become more accessible and validated, they will play a key role in telemedicine and remote monitoring, particularly inunderserved or rural areas where specialized kidney care may be limited. Despite these promising prospects, challenges persist. Issues related to data privacy, regulatory concerns, and the interpretability of ML models need to be addressed before AI systems can be fully integrated into clinical practice. Furthermore, improving the generalizability of these models to diverse populations and healthcare settings is essential for their widespread adoption. However, as global datasets become more available and as regulatory frameworks evolve to accommodate AI technologies, machine learning will continue to transform kidney disease diagnosis and treatment. In conclusion, the future scope of machine learning in the detection and management of kidney diseases is vast and filled with transformative potential. With ongoing advancements in AI, ML, and data integration, these technologies will not only enhance the accuracy and efficiency of kidney disease diagnoses, but also pave the way for personalized, predictive, and preventive care, significantly improving patient outcomes worldwide.

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