A Project Report On

Kidney Disease Detection Using Deep learning

Submitted in partial fulfilment for the
degree of Bachelor of Technology in
Data Science

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Declaration

We, **Sharvaree Bamane, Jyotsna Chitte, Sonal Ghuge**, hereby declare that the work presented in this *project* entitled "*Kidney Disease Detection using Deep learning*" is entirely my own. The content of this *project* has been generated through my independent efforts, research, and scholarly contributions. We further declare that:

1. **Originality:**
   - The ideas, concepts, and contributions presented in this work are solely the result of our own intellectual endeavors.
2. **Authenticity:**
   - All data, figures, tables, and findings presented in this *project* are genuine and have not been fabricated or manipulated.
3. **No Use of AI Tools:**
   - We have not used any AI-based tools to generate significant portions of this *project* including, but not limited to content, research objectives, hypotheses, and analysis.
4. **No Plagiarism:**
   - We have properly cited and referenced all external sources and works consulted during the preparation of this *research project.*
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5. **Independent Work:**
   - This work has been conducted independently, without any collaboration or assistance that would compromise the originality of the content.
6. **Academic Integrity:**
   - We have adhered to the principles of academic integrity and ethical research throughout the entire process of producing this *research project.*

We understand the consequences of academic dishonesty and affirm that this declaration accurately reflects the nature and authenticity of our work.

Date: *29-05-2024*

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Sharvaree Bamane

Signature: ______________________
Jyotsna Chitte

Signature: ______________________
Sonal Ghuge

Certificate

This is to certify that Sharvaree Bamane , Jyotsna Chitte and Sonal Ghuge has completed the major project report on the topic "Kidney Disease Detection Using Deep Learning" satisfactorily in partial fulfillment for the Bachelor of Technology in Data Science under the guidance of prof. Poonam Dharpawar during the year 2023-24 as prescribed by S.N.D.T Women's University,Mumbai

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Abstract

Kideny Disease complaint (KD) is a growing health problem worldwide. Early discovery of KD is pivotal for the effective operation of the complaint. In recent times, convolutional neural networks(CNN) have shown great eventuality for image recognition and bracket tasks. In this study, we propose a CNN- grounded system for the Ditection of KD from Kidney ultrasound images. The methodology involves preprocessing the ultrasound images to remove noise and vestiges. The preprocessed images are also fed into a CNN model conforming of multiple convolutional layers, pooling layers, and completely connected layers. The performance of the model is estimated using colorful criteria similar as delicacy, perfection, recall, and F1score.The results show that the proposed CNN- grounded system achieves high delicacy and can effectively classify ultrasound images as KD or non-KD. This system has the implicit to be a useful tool for the early discovery and operation of KD, which can ultimatly improve patient autcomes.

The impact of technological advancement, particularly machine literacy, on health can be seen in the effective analysis of different habitual conditions that allows for more precise opinion and effective treatment. People aged 60 and over are most affected by order complaint, a seriouscondition linked to ageing, hypertension, and diabetes. Beforehand opinion of KD enables cases to admit immediate treatment, which slows the complaint's further development. This study employs the machine literacy ways of artificial neural networks, support vector machines, and k- Nearest Neighbor to identify KD beforehand. The significance of detecting these constantly fatal ails reflects the significance of AI. These four processes of image preprocessing, Feature Extraction and opinion are used to identify the type of complaint. complication Neural Network(CNN), which has a number of Predication based layers, is used for categorization and image preprocessing to ameliorate the image's quality. At the very end, the stoner is encouraged to get a cure.

Keywords: *kidney Disease Detection using Deep learning, Scanned Images, Image Processing,Confusion matrix, Predict Disease, Etc...*

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Chapter 1

Introduction

Kidney disease represents a significant global health challenge, affecting millions of individuals and exerting substantial burdens in terms of morbidity and mortality. The timely detection and accurate classification of kidney abnormalities are imperative for effective disease management and treatment. Recent advancements in medical imaging and computational techniques have paved the way for innovative approaches to address these challenges. In particular, the integration of image processing methodologies with state-of-the-art deep learning frameworks such as TensorFlow and Keras has emerged as a promising avenue for enhancing the diagnosis and classification of kidney diseases. Kidney disease encompasses a wide spectrum of conditions, ranging from benign cysts to malignant tumors, each posing unique diagnostic and therapeutic challenges. The prevalence of kidney disease is staggering, with millions of individuals worldwide suffering from various forms of renal dysfunction. Moreover, the consequences of untreated or inadequately managed kidney disease can be severe, leading to complications such as kidney failure, cardiovascular disease, and even premature death. Therefore, there is a pressing need to improve the detection and classification of kidney abnormalities to mitigate these adverse outcomes.
Traditional diagnostic methods, including ultrasound and X-ray , play a crucial role in visualizing kidney anatomy and detecting abnormalities. However, these modalities are not without limitations. Interpretation of imaging data can be subjective and time-consuming, relying heavily on the expertise of the interpreting

clinician. Moreover, subtle or early-stage abnormalities may go unnoticed, potentially leading to diagnostic errors or delays in treatment initiation. Therefore, there is a growing demand for more objective, efficient, and accurate diagnostic tools to augment traditional imaging approaches. Deep learning algorithms, particularly convolutional neural networks (CNNs), have demonstrated remarkable capabilities in extracting complex patterns and features from medical imaging data. By leveraging large datasets, deep learning models can learn to discern subtle nuances and variations in images, enabling automated detection and classification of pathological conditions with high accuracy. TensorFlow and Keras, as leading open-source frameworks for machine learning and neural network development, provide powerful tools for implementing sophisticated deep learning architectures tailored to specific medical imaging tasks.

The proposed approach involves several key steps aimed at enhancing the detection and classification of kidney abnormalities. Firstly, a diverse dataset comprising images of normal kidneys and various pathological conditions, including cysts, tumors, and stones, is collected and meticulously curated. Preprocessing techniques, such as resizing, normalization, and data augmentation, are applied to enhance the quality and diversity of the dataset, thereby facilitating robust model training. Subsequently, a CNN architecture is designed using TensorFlow and Keras, tailored to the complexities of kidney imaging data. The CNN is trained on the prepared dataset using supervised learning techniques, wherein it learns to differentiate between different classes of kidney abnormalities based on the features present in the input images. The training process involves iteratively adjusting model parameters to minimize prediction errors and optimize performance. Once trained, the model undergoes rigorous evaluation using separate validation and test datasets to assess its generalization ability and performance metrics, including accuracy, precision, recall, and F1-score. Fine-tuning and optimization techniques may be employed iteratively to further enhance the model's performance.

1.1 Motivation

The provocation of this study is to develop a CNN- grounded system for the detection of KD from ultrasound images of the feathers. The proposed system involves preprocessing of ultrasound images to remove noise and vestiges. The preprocessed images are also fed into a CNN model conforming of multiple convolutional layers, pooling layers, and completely connected layers. The model is trained using a dataset of ultrasound images of feathers from cases with and without KD. The performance of the model is estimated using colorful criteria similar as delicacy, perfection, recall, and F1 score. The results show that the proposed CNN grounded system achieves high delicacy and can effectively classify ultrasound images as KD or non-KD. The proposed system has the implicit to be a useful tool for the early discovery and operation of KD. It can help clinicians make further accurate judgments and develop individualized treatment plans for cases with KD. Overall, this study demonstrates the eventuality of CNN in medical image analysis and highlights the significance of using advanced ways for the early discovery and operation of Kidney diseases.renal complaint is an irrecoverable order disease that raises the threat of a wide range of ails, including heart failure, anemia, and bone complaint. The feathers are incredibly protean. still, kidney damage is not immediately obvious due to symptoms. Cases constantly don't have symptoms until the condition is nearly terminal.
Avoiding symptoms is a treatment option for some Kidney diseases. Restoring a few kidney functions, it aids patients in preventing the condition from getting worse.Dialysis and kidney transplantation are two of the main treatments for end-stage kidney disease, particularly in cases with CKD. More than 800 million people worldwide suffer from kidney disease, which is a progressive condition. Due to the high cost of treatment, only 10of patients receive dialysis or a kidney transplant, and it is predicted that the number of kidney failure cases will rise disproportionately in developing nations like China and India, where the elderly population is growing.

1.2 Objectives

The objectives of kidney disease (KD) detection software are to:
1. Identify individuals at risk: The software should be able to identify individuals who are at risk of developing KD based on their medical history, family history, and other risk factors.
2. Detect KD early: The software should be able to detect KD in its early stages, when treatment is most effective in slowing the progression of the disease.
3. Provide accurate diagnosis: The software should be able to accurately diagnose KD by analyzing laboratory test results, medical history, and other relevant information.
4. Monitor kidney function: The software should be able to monitor changes in the kidney function over time, allowing healthcare providers to adjust treatment plans as needed.
5. Personalize treatment: The software should be able to provide personalized treatment recommendations based on an individual's medical history, current health status, and other factors.
6. Integrate with electronic health records (EHR): The software should be able to integrate with EHR to access relevant patient data, such as laboratory test results and medical history.
7. Educate patients: The software should be able to educate patients about KD, including its causes, symptoms, and treatment options.
8. Improve patient outcomes: The ultimate objective of KD detection software is to improve patient outcomes by identifying KD early and providing personalized, effective treatment plans that slow the progression of the disease and prevent complications. By achieving these objectives, KD detection software can help healthcare providers to identify and treat KD early, leading to improved patient outcomes and reduced healthcare costs.

1.3 Problem Statement

Detecting kidney diseases through image processing involves utilizing TensorFlow and Keras to classify images into normal, cyst, tumor, and stone classes. This project aims to develop a robust algorithm capable of accurately identifying abnormalities in kidney images, facilitating early diagnosis and treatment. Leveraging deep learning techniques, such as convolutional neural networks (CNN), the system will analyze various features within the images to differentiate between different pathological conditions. By automating the detection process, this technology offers a faster and more efficient means of identifying kidney diseases, potentially improving patient outcomes through timely intervention.

1.4 Scope of the Project

The scope of kidney disease (KD) detection software is quite broad, as it involves the use of technology to aid in the detection, diagnosis, and treatment of KD. The software can help to identify individuals who are at risk of developing KD, enabling healthcare providers to intervene early and prevent or slow the progression of the disease. The software can monitor changes in kidney function over time, alerting healthcare providers to any signs of progression or worsening of the disease. The scope of KD detection software is not limited to a specific type of technology or platform and can include various tools such as mobile apps, web-based platforms, and clinical decision support systems. The ultimate goal of the software is to improve the detection and management of KD, leading to improved patient outcomes and reduced healthcare costs.kidney disease (KD) detection software has several applications in the health care industry. Some of the most common applications of KD detection software include:

- The software can provide personalized treatment recommendations based on an individual's medical history, current health status, and other factors.
- The software can provide educational resources to patients and healthcare providers,helping to raise awareness about KD, its causes, symptoms, and treatment options.
- The software can integrate with EHR to access relevant patient data, such as lab oratory test results and medical history, allowing healthcare providers to make more informed decisions about diagnosis and treatment.
- KD detection software can be used by public health officials and healthcare organizations to identify populations at risk for KD and implement targeted prevention and treatment programs.
- KD detection software can be used in research studies to identify potential risk factors for KD and develop new treatment approaches.

The applications of KD detection software are not limited to these areas and can vary depending on the specific needs of healthcare providers, patients, and public health officials. Overall, KD detection software can help to improve the detection and management of KD, leading to improved patient outcomes and reduced healthcare costs.

Chapter 2

Literature Review

Review of Literature

A literature review is an essential part of the exploration process, furnishing a thorough understanding of the being knowledge and serving as a foundation for new exploration. It helps experimenters to make upon the work of others and avoid duplicating efforts ensuring that exploration is conducted in a methodical and effective manner.

1. Development of order Disease Prediction Using Machine Learning [2] exploration paper published at International Conference on Intelligent Data Communication Technologies on 2019 proposed creating a system for prognosticating the presence of KD using machine literacy styles including Naive Bayes, K- Nearest Neighbor, Logistic Retrogression, Decision Tree, Random Forest, and Multi-Layer Perceptron Algorithm. These are used, and the effectiveness of each is estimated in relation to the issues for delicacy, perfection, and recall. The system is eventually enforced using Random Forest.

2.M.N. Amin,A. Al Imran andF.T. Johora etal. dissect model performance on real(imbalanced) data and model performance on oversampled(balanced) data using logistic retrogression and feed forward neural networks.[3] Feed forward neural networks showed the stylish results for both real and oversampled data, with0.99 Recall,0.97 Precision,0.99 F1- Score and0.99 AUC score.

3. A dataset from the UCI machine literacy depository containing data on

roughly 400 cases is used by Kayaalp etal. to study order complaint using mongrel bracket approaches.[4] They choose the most material point in the dataset using the relief and gain rate approach and the support vector machine and KNN classifier. They get to the conclusion that, in terms of fmeasure, perfection, and discrepancy matrix, the KNN approach outperforms other algorithms for a set of features.

4. To identify KD, A. Salekin and J. Stankovic tested three classifiers: neural network,random forest, and K-nearest neighbors. They made use of a dataset from UCI with 400 patients and 24 attributes.[1] The attributes that accurately identify this disease have been discovered by the use of the wrapper approach in a feature reduction study.They may predict the presence of KD with a.98 F1 and a 0.11 RMSE by taking factors like albumin, specific gravity, diabetes mellitus, hemoglobin, and hypertension into account.

5. Accelerated cardiovascular disease is a frequent complication of renal disease.kidney disease promotes hypertension and dyslipidemia, which in turn can contribute to the progression of renal failure.[8] Furthermore, diabetic nephropathy is the leading cause of renal failure in developed countries. Together, hypertension, dyslipidemia,and diabetes are major risk factors for the development of endothelial dysfunction and the progression of atherosclerosis.[7] Inflammatory mediators are often elevated and the renin-angiotensin system is frequently activated in chronic kidney disease, which likely contributes through enhanced production of reactive oxygen species to accelerated atherosclerosis observed in kidney disease.

6. In this narrative review,[11] we studied the association of threat factors for order complaint(KD) and KD frequence at an ecological position and describe implicit reasons for transnational differences in estimated KD frequence across Europeancountries.We set up substantial variations in threat factors for KD similar as in the frequence of diabetes mellitus, rotundity, raised blood pressure, physical inactivity, current smoking, and swab input per day. In general, the countries with a advanced KD frequence also had a advanced average score on KD threat factors and vice versa.[3] There was no association between cardiovascular mortality rates and KD frequence. In countries with a high CKD frequence, the forestallment of noninfectious conditions may be considered important, and, thus, all five public response systems(e.g. an operationalnational policy, strategy or action plan to reduce physical inactivity and/ or promote physical exertion) have been enforced.

likewise, both the diversity in study styles to assess KD frequence as well as the transnational differences in the perpetration of life measures will contribute to the observed variation in KD frequence. A robust public health approach to reduce threat factors in order to help KD and reduce KD progression threat is demanded and will haveco-benefits for othernon-communicable conditions.

7. Endothelium is the unique filling absolutely all cardiovascular system organs of the body.[10] Endothelial cells form a hedge between the blood and apkins, perform a number of important nonsupervisory functions, synthesizing and releasing a wide range of biologically active substances. The strategic position of the endothelium allows it to be sensitive to haemodynamic changes as well as to the signals carried by the blood and signals of underpinning apkins. Balanced release of biologically active substances contributes to homeostasis conservation.[5] The data concerning the multiple mechanisms of endothelium participation in the origin and development of colorful pathological conditions is accumulated so far. The part of endothelial dysfunction in the development of conditions similar as atherosclerosis, arterial hypertension, habitual heart failure, diabetes mellitus, habitual obstructive pulmonary complaint, habitual order complaint, seditious bowel complaint, and others has been proven lately.

8. The frequence of order complaint (KD) increases annually in the present script of exploration.[8] One of the sources for farther remedy is the KD vaticination where the Machine literacy ways come more important in medical opinion due to their high delicacy bracket capability. In the recent history, the delicacy of bracket algorithms depends on the proper use of algorithms for point selection to reduce the data size. In this paper, miscellaneous Modified Artifical Neural Network has been proposed for the early discovery, segmentation, and opinion of renal failure on the Internet of Medical effects(IoMT) platform.[15] likewise, the proposed ANN is classified as a Support Vector Machine and Multilayer Perceptron(MLP) with a Backpropagation(BP) algorithm. The proposed algorithm works grounded on an ultrasound image which is denoted as a preprocessing step and the region of order interest is segmented in the ultrasound image. In order 9 segmentation, the proposed ANN system achieves high delicacy and significantly reducing the time to delineate the figure.

9. KD, with its high frequence, morbidity and mortality,[16] is an important

public health problem. With ¡3 of land mass, India hosts 17 of the Earth's population. Large figures of cases below the poverty line, low gross domestic product, and low financial allocations for health care have led to sour issues. also, KD and other noninfectious conditions have frequently been ignored in the face of patient challenges from and competition for coffers for transmissible conditions and high child and motherly mortality.

Chapter 3

Research Methodology

3.1 Block Digram

The ML models were trained and tested grounded on readily accessible variables, including the baseline characteristics and routine ultrasound images. Results attained from this study suggest not only the feasibility of ML models in performing this clinically critical task, but also the eventuality in easing individualized drug. Rather of doing multiple clinical test similar as blood test, urine test, this system will work on ultrasound report of order which will reuse the report and give the result of order complaint is present or not.

The illustration below shows the system's block diagram. The dataset contains ultrasound images of the cases. The data processing and point selection block processes the image through a machine learning algorithm and further annotates the data to the bracket section. The bracket section verifies the annotated data using a CNN system and provides the factual outcome of the report. There are three stages in the intricate block illustration in the figure. The primary responsibility of the original stage of data collection and transmission is to collect data from ultrasonic film, mobile devices, etc., in the named size and resolution. From the dataset for the training set, the model architecture was first constructed with exceptional delicacy in mind. The training dataset was used in the third step of the procedure, and numerous images were also used to test or validate the model. Finally, the model was added to a web runner for use. In order to take the proper action, the system will identify whether the symptoms are showing up on the ultrasound report. We'll take the digital camera image that needs to be uploaded and run the CNN algorithm to determine whether the complaint is present or not.

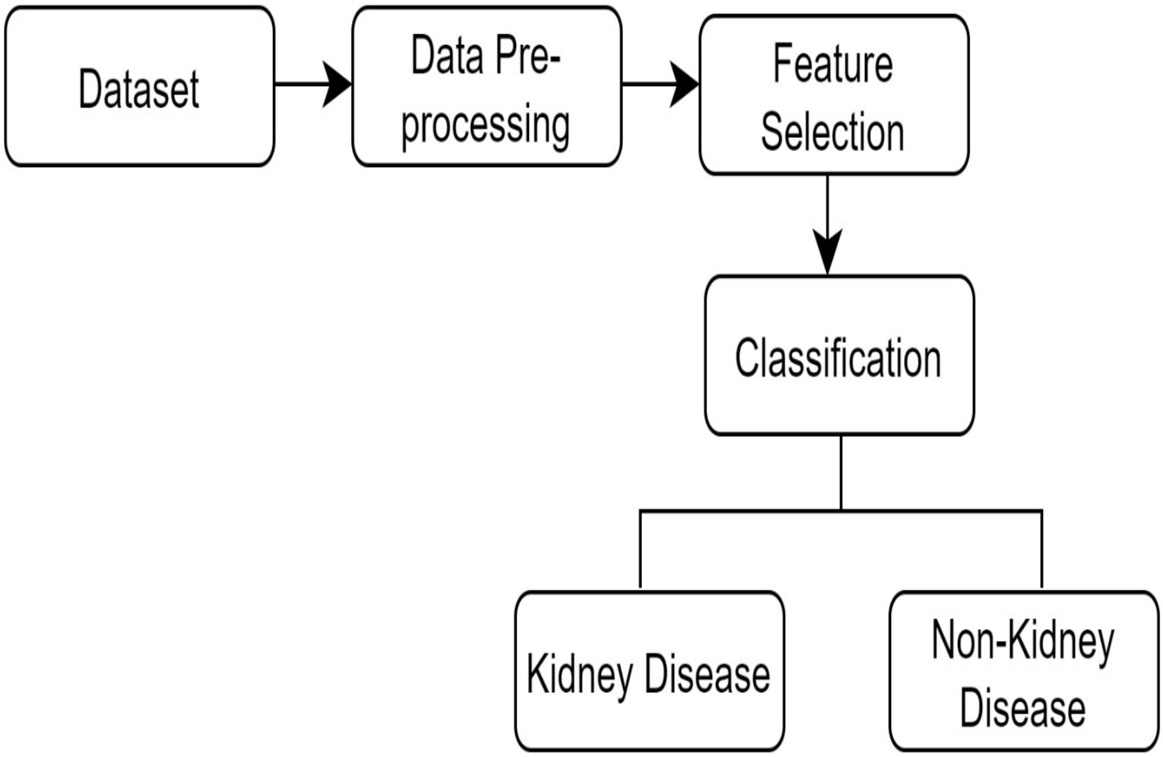


Figure 3.1: The Block diagram of Kidney Disease prediction system using CNN

3.2 Convolutional Neural Network

A Convolutional Neural Network (CNN) is a type of deep learning algorithm particularly well-suited for image recognition and processing tasks. CNNs are designed to process structured arrays of data, such as images. They excel at detecting patterns in input images, such as lines, curves, circles, and even complex structures like eyes and faces. This characteristic is what makes convolutional neural networks so robust for computer vision. CNNs can directly process raw images without the need for preprocessing.

A convolutional neural network is a feedforward neural network, often with up to 20 layers. The power of a convolutional neural network lies in a specific type of layer called the convolutional layer. CNNs consist of multiple convolutional layers stacked on top of each other, each capable of recognizing increasingly complex shapes. With just three or four convolutional layers, it's possible to recognize handwritten digits, while with 25 layers, it's possible to distinguish between human faces. The goal of this field is to enable machines to perceive the world as humans do, interpret it similarly, and use this understanding for various tasks such as image and video recognition, image analysis and classification, media recreation, recommendation systems, natural language processing, etc.

The architecture of a CNN is primarily a list of layers that transform the 3-dimensional image volume (width, height, and depth) into a 3-dimensional output volume. One important point to note is that every neuron in the current layer is connected to a small patch of the input from the previous layer, which is akin to overlaying a neural network grid on the input image. The network uses filters, which are essentially feature extractors that detect features like edges and corners.

The layers (INPUT - CONV - RELU - POOL - FC) are used to construct Convolutional Neural Networks (CNNs). CNNs are a type of deep learning model designed to process data with a grid pattern, such as images. They are inspired by the organization of the animal visual cortex and are designed to automatically and adaptively learn spatial hierarchies of features, from low- to high-level patterns.

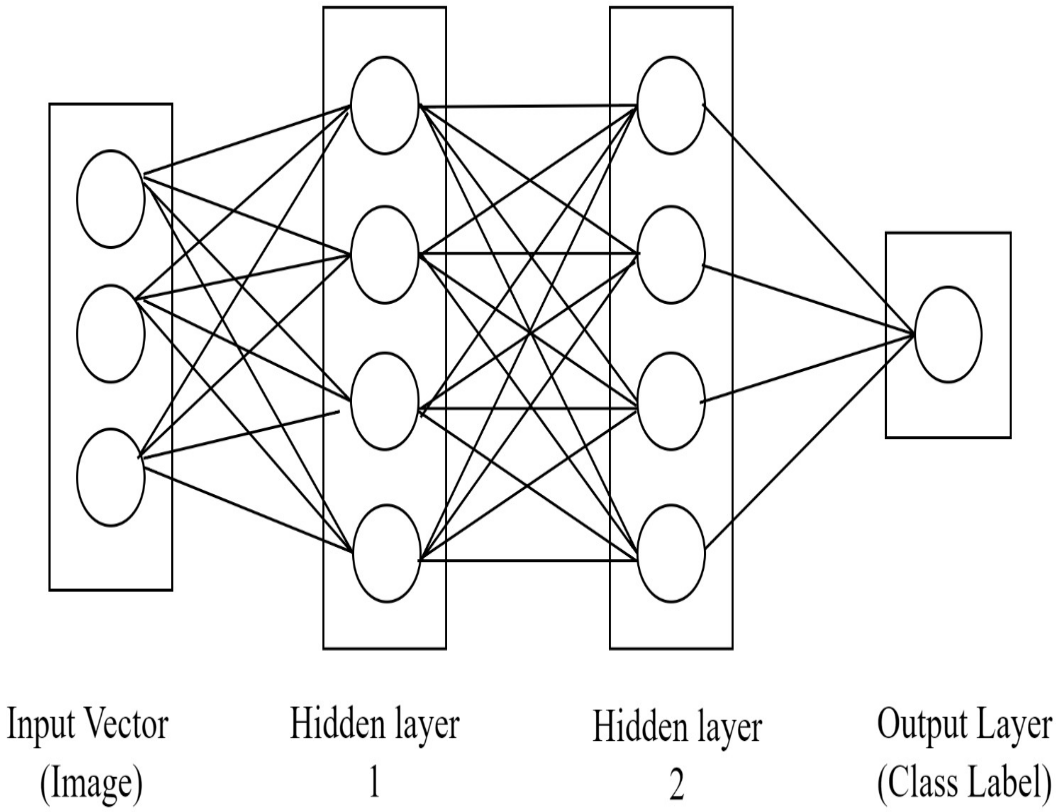


Figure 3.2: CNN Architecture

1. INPUT: As the name implies, this layer holds the raw pixel values of the image, representing the image exactly as it is. For example, INPUT($64 \times 64 \times 3$) represents a 3-channel RGB image with dimensions 64x64x3.

2. CONV: This layer is one of the fundamental building blocks of CNNs, as most of the computation is done in this layer. For example, applying 6 filters to the INPUT($64 \times 64 \times 3$) would result in a volume of ($64 \times 64 \times 6$) 6).

3.RELU: Also known as the Rectified Linear Unit layer, this layer applies an activation function to the output of the previous layer, adding non-linearity to the network.

4. POOL: The Pooling layer is another building block of CNNs. Its main task is downsampling, which means it operates independently on each slice of the input and spatially resizes it.

5. FC: The Fully Connected layer, or more specifically the Dense layer, is used to compute the class scores. The output volume of this layer is typically of size 1 * 1 * L, where L is the number of classes.

3.3 CNN Image Classifier

A CNN (Convolutional Neural Network) image classifier is a type of neural network designed to classify images into different categories or classes. It uses convolutional layers to extract features from the input image and then uses fully connected layers to produce a final output representing a probability distribution over possible classes. Here are the steps followed in the Image classifier technique:

1. Data preparation: Gather a dataset of images labeled with their corresponding classes (e.g., stone, tumor, cyst, Normal). Divide the dataset into training, validation, and testing sets.

2. Preprocessing: Preprocess the images by resizing them to a uniform size, normalizing the pixel values, and applying data augmentation techniques such as random rotations, flips, and crops. This helps increase the diversity of the training data and prevent overfitting.

3. Model architecture: Choose a CNN architecture appropriate for the task at hand. Customize the architecture by adjusting the number of layers, filter sizes, and other hyperparameters as needed.

4. Training: Train the model using the training set of images and their corresponding labels. Use a loss function such as cross-entropy to measure the difference between the predicted and actual labels, and an optimizer such as SGD or Adam to update the model parameters.

5. Validation: Evaluate the performance of the model on the validation set of images and their corresponding labels. Monitor metrics such as accuracy, precision, and recall to track the model's performance over time. Use techniques such as early stopping and learning rate annealing to prevent overfitting and improve convergence.

6. Testing: Once the model has been trained and validated, evaluate its performance on the testing set of images and their corresponding labels. This provides a final estimate of the model's accuracy on unseen data.

7.Deployment: Deploy the model in a production environment, either by using it to classify new images in real-time or by integrating it into a larger system such as a web application or mobile app.

3.4 Data Collection Preprocessing

3.4.1 Data Collection:

Data collection is a critical component of our project on kidney disease detection. Kaggle serves as a valuable platform for accessing datasets pertinent to our research. The platform offers a diverse array of datasets covering various aspects of kidney disease, including clinical data, lab results, and imaging studies. By leveraging Kaggle, we can access well-documented datasets that provide essential information about the patients' demographics, medical history, and diagnostic test results. Furthermore, Kaggle's community forums and kernels offer valuable insights and methodologies for analyzing and interpreting the dataset, enhancing the quality and depth of our research.

3.4.2 Preprocessing:

1.Grayscale Image:

A grayscale image generally uses a range of argentine tones to represent the varying situations of brilliance in the original image. It retains the information about the relative brilliance of different corridor of the image. Grayscale images are frequently used when you want to save the full range of argentine situations in the original image. They're useful in operations where the different tones of argentine convey important information, similar as in medical imaging, shooter raphy, or image analysis.

2.Normalizing Image:

Normalizing image typically involves adjusting the pixel values so that they fall within a specific range or have a specific statistical distribution. The primary purpose of normalizing grayscale images is to enhance the contrast and make it easier to process or analyze the image data.Overall,normilizing images is a preprocessing step that helps in improving the quality of the image data, making it more suitable for various image processing tasks,machine learning, and analysis. It enhances contrast, reduces variability,and can make the data more amenable to statistical analysis and machine learning algorithm.

3.Resize Image:

resizing a image is a common image processing task that allows you to adjust the image's dimensions for various purposes, including display, file size reduction,consistency, memory and processing efficiency, printing, and more.It's important to maintain the aspect ratio when resizing to ensure the image retains its original proportions.

4.Augmentation Image:

Image augmentation is a technique used to create variations of the original image by applying various transformations. These transformations help enhance the training of machine learning models and improve their ability to generalize from a limited dataset.augmentation techniques is to expose the model to a wide range of variations in the data, making it more adaptable and capable of generalizing well to unseen examples. This is particularly important in machine learning tasks like image classification, object detection, and segmentation, where the model needs to handle a variety of real-world conditions and scenarios

3.5 Methodology

Kidney disease detection is crucial for early diagnosis and effective treatment. This proposed methodology utilizes image processing techniques implemented with TensorFlow and Keras to classify kidney images into four classes: normal, cyst, tumor, and stone.

1, Data Acquisition: A dataset containing a variety of order images representing different classes (normal, cyst, tumor, and stone) is collected. These images can be obtained from medical databases or through collaboration with healthcare institutions.

2.Preprocessing: Image preprocessing techniques are applied to enhance image quality and remove noise. This may include resizing, normalization, and noise reduction to ensure uniformity and improve the effectiveness of subsequent processing steps.

3.Feature Extraction: Features relevant to order complaint diagnosis are extracted from preprocessed images. These features could include texture, shape, and intensity characteristics that distinguish between different classes of order abnormalities.

4.Model Development: A convolutional neural network (CNN) architecture is designed using TensorFlow and implemented with Keras. The CNN architecture is trained on the extracted features using a labeled dataset. Transfer learning techniques, such as fine-tuning pre-trained models like VGG or ResNet, can also be employed to improve performance, especially with limited data.

5.Model Training and Validation: The dataset is divided into training, validation, and testing sets. The CNN model is trained on the training data and validated on the validation set to tune hyperparameters and prevent overfitting.

6.Evaluation: The trained model's performance is evaluated using the testing dataset to assess its sensitivity, specificity, recall, and F1-score. Confusion matrices and ROC curves may also be analyzed to understand the model's performance across different classes.

7.Deployment: Once the model demonstrates satisfactory performance, it can be deployed for real-world order complaint detection operations. This could involve integration into medical imaging systems or development of a standalone application for healthcare professionals. By employing this methodology, accurate and effective order complaint detection can be achieved, enabling timely intervention and improved patient outcomes. Additionally, the use of TensorFlow and Keras provides a flexible and scalable framework for developing robust image classification models.

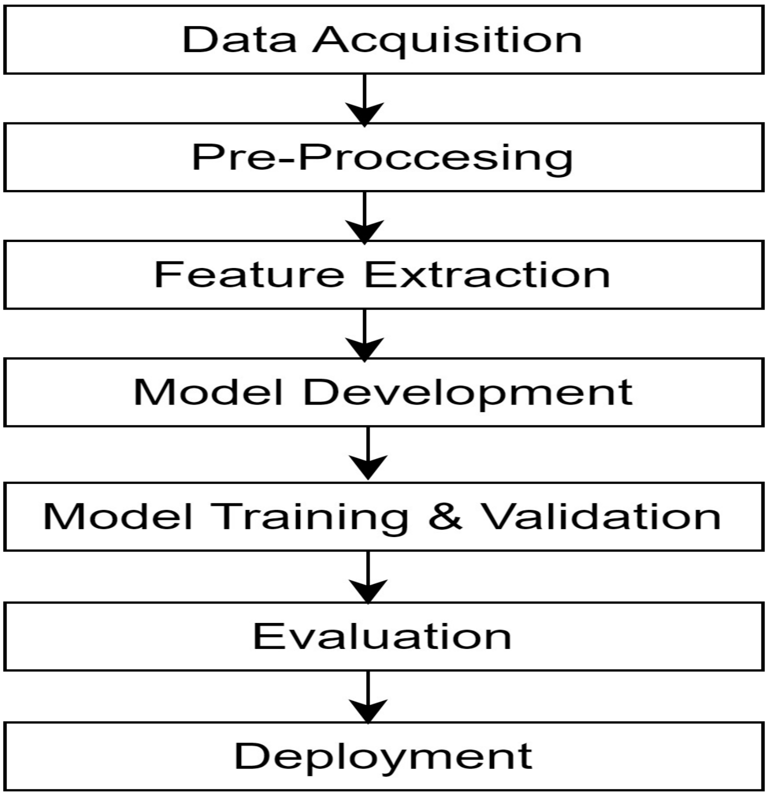


Figure 3.3: Proposed Methodology

3.5.1 WORKING

Step1: Detecting kidney diseases through image processing using TensorFlow and Keras involves several steps: preprocessing the images, building a deep learning model, training it, and then evaluating its performance. The first step is to preprocess the images. This involves tasks like resizing, normalization, and augmentation to enhance the quality and variability of the dataset. Then, the dataset is split into training, validation, and testing sets.

Step 2:a deep learning model is built using TensorFlow and Keras. Convolutional Neural Networks (CNN) are commonly used for image classification tasks due to their ability to automatically learn relevant features from images. The model architecture typically consists of multiple convolutional layers followed by pooling layers to extract features and reduce dimensionality, and then fully connected layers for classification.

Step 3: After building the model, it is trained on the preprocessed dataset using the training set. During training, the model adjusts its parameters using an optimization algorithm (e.g., stochastic gradient descent) to minimize the classification error. The performance of the model is monitored using the validation set to avoid overfitting.

Step 4: Once training is complete, the model is evaluated using the testing set to assess its performance on unseen data. Evaluation metrics such as accuracy, precision, recall, and F1-score are computed to measure the model's effectiveness in classifying kidney images into normal, cyst, tumor, and stone classes.

Step 5: Finally, the trained model can be deployed in real-world applications for kidney disease detection. This could involve integrating it into medical imaging systems to assist radiologists in diagnosing kidney diseases more accurately and efficiently. In summary, kidney disease detection using image processing with TensorFlow and Keras involves preprocessing the images, building and training a deep learning model, evaluating its performance, and deploying it for real-world use, potentially improving the diagnosis and treatment of kidney diseases.

3.6 Long Short-Term Memory

LSTM stands for long short- term memory networks, used in the field of Deep Learning. It's a variety of intermittent neural networks(RNN) that are suitable of learning long- term dependences, especially in sequence prophecy problems. LSTM has feedback connections, i.e., it's suitable of recovering the entire sequence of data, piecemeal from single data points analogous as images. This finds operation in speech recognition, machine paraphrase, etc. LSTM is a special kind of RNN, which shows outstanding performance on a large variety of problems. The central part of an LSTM model is held by a memory cell known as a ' cell state ' that maintains its state over time. The cell state is the perpendicular line that runs through the top of the below illustration.It can be visualized as a conveyor belt through which information flows without alteration.

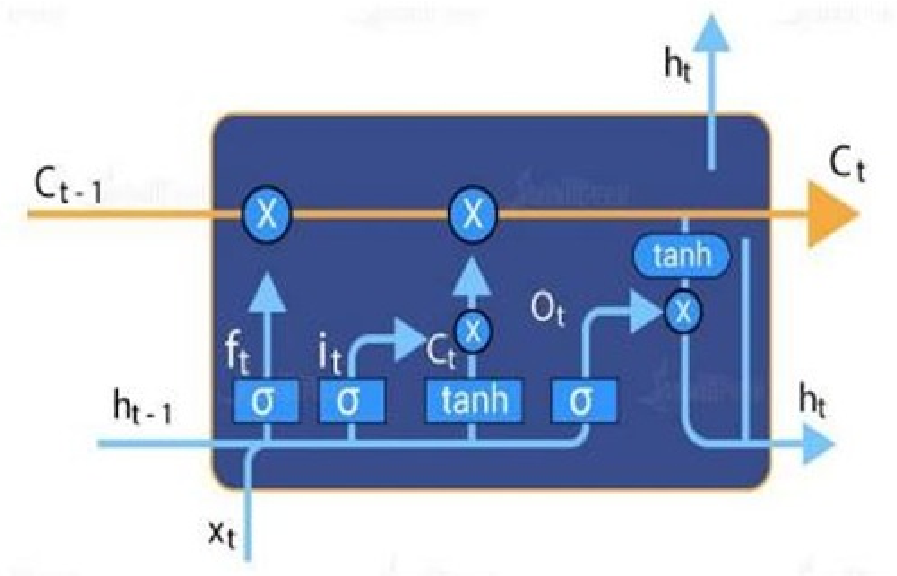


Figure 3.4: LSTM Architecture

LSTM models are a subtype of intermittent Neural Networks. They're used to fete patterns in data sequences, similar as those that appear in detector data, stock prices, or natural language. A special armature allows the LSTM model to decide whether to retain former information in short- term memory or discard it. Information can be added to or removed from the cell state in LSTM and is regulated by gates. These gates voluntarily let the information inflow in and out of the cell. It contains a pointwise addition operation and a sigmoid neural net subcaste that help the medium. The sigmoid subcaste gives out figures between zero and one, where zero means ‘ nothing should be let through, ’ and one means ‘ everything should be let through. ’ LSTM neural networks are able of working multitudinous tasks that aren’t soluble by 22 former literacy algorithms like RNNs. Long- term temporal dependences can be captured effectively by LSTM, without suffering important optimization hurdles. This is used to address the high- end problems.

Chapter 4

Realisation/Implementation of the proposed Predictive Analytics in Cardiology:towards early detection of Kidney diseases

Detecting kidney diseases through image processing involves utilizing TensorFlow and Keras to classify images into normal, cyst, tumor, and stone classes. This project aims to develop a robust algorithm capable of accurately identifying abnormalities in kidney images, facilitating early diagnosis and treatment. Leveraging deep learning techniques, such as convolutional neural networks (CNN), the system will analyze various features within the images to differentiate between different pathological conditions. By automating the detection process, this technology offers a faster and more efficient means of identifying kidney diseases, potentially improving patient outcomes through timely intervention.

4.1 Design and Implementation

4.1.1 Flow Chart of KDD System

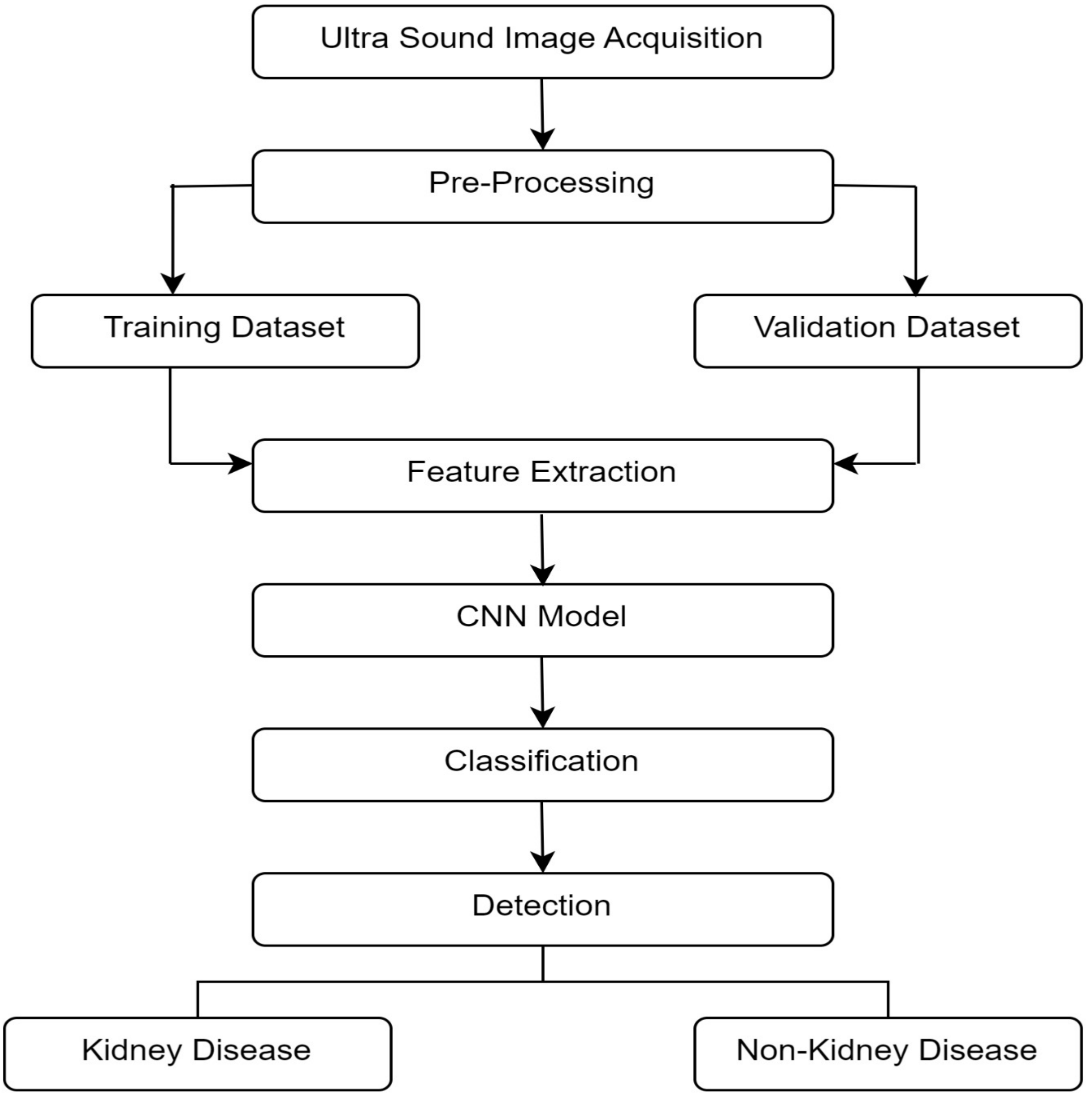


Figure 4.1: Flow Chart of KDD System

4.1.2 Use Case Diagram of KDD System

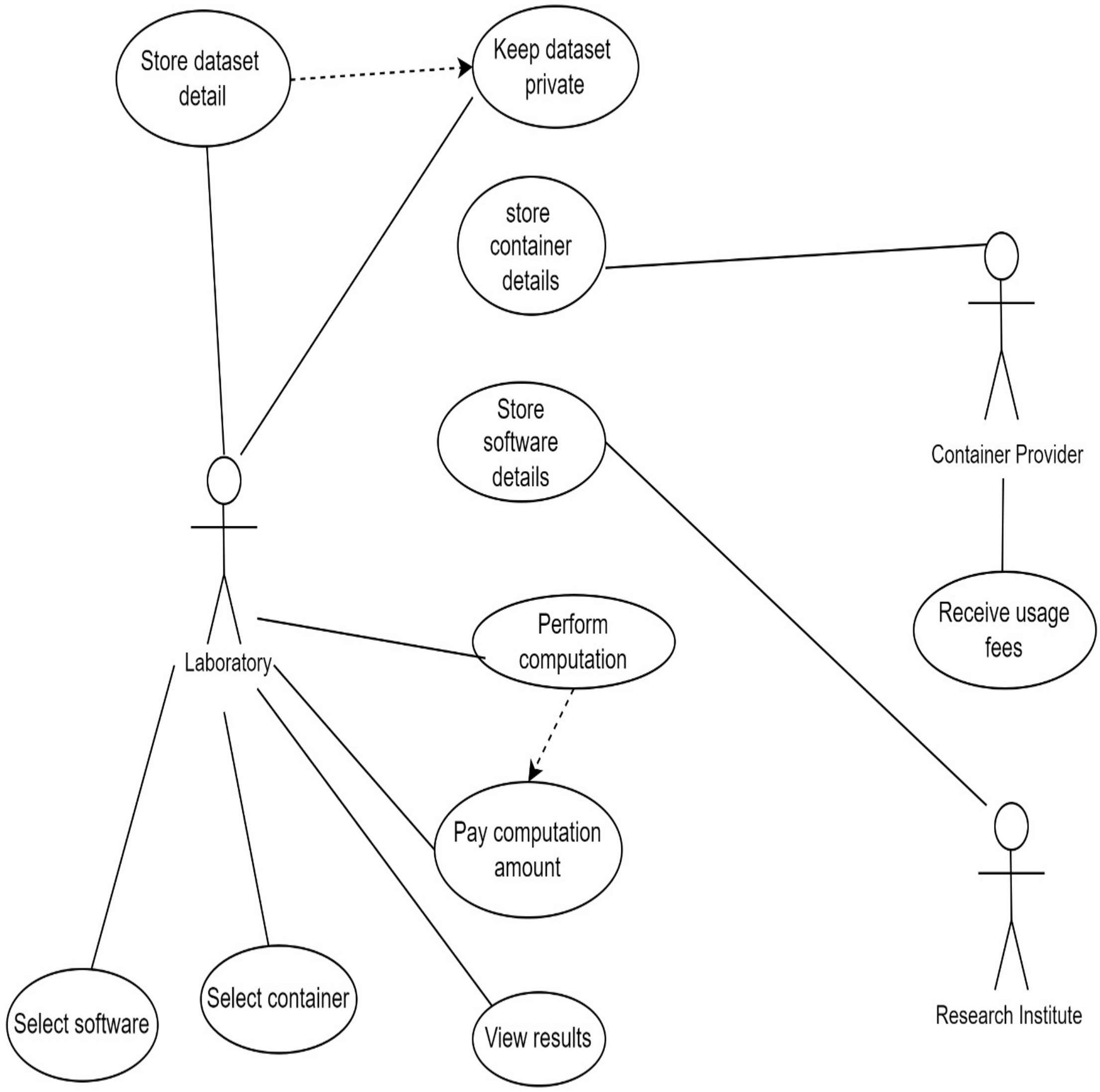


Figure 4.2: Use Case Diagram of KDD System

4.2 Import Libraries

There is following Libraries are used in this Kidney Disease:

1.keras.preprocessing.image: This module provides utilities for image data preprocessing and augmentation. The 'ImageDataGenerator' class is particularly useful, as it allows you to create flexible data generators for training deep learning models with image data. Data augmentation techniques such as rotation, shearing, zooming, and flipping can be applied to the images in real-time, which helps in increasing the diversity of the training data and improving the generalization of the model.

2.keras.utils: This module contains utility functions that are commonly used in deep learning tasks. 'load img' and 'img to array' are useful for loading image files and converting them into arrays, which are common preprocessing steps in computer vision tasks. These functions help in preparing the input data for training or inference in a deep learning model.

3. keras.models: The 'Sequential' class in this module is used to create a sequential model, which is a linear stack of layers. This type of model is suitable for building feedforward neural networks where the output of each layer is fed as input to the next layer. The 'Model' class is used to create more complex models with multiple inputs and outputs, allowing for more flexibility in model architecture.

4.keras.layers: This module contains a wide range of layer types that can be used to build deep learning models. Convolutional layers ('Conv2D') are commonly used in image processing tasks for feature extraction. Pooling layers ('MaxPool2D') are used for downsampling feature maps. Dense layers ('Dense') are fully connected layers that are often used in the final layers of a neural network for classification or regression tasks. Dropout layers ('Dropout') are used for regularization, which helps in preventing overfitting.

5.matplotlib.pyplot: Matplotlib is a popular plotting library in Python. The 'pyplot' module provides a simple interface for creating various types of plots and charts, such as line plots, bar plots, and histograms. It is commonly used for visualizing the performance of deep learning models, such as plotting training and validation loss curves.

6.tensorflow.keras.layers and tensorflow.keras.applications: These modules provide

additional layer classes and pre-trained models from TensorFlow's implementation of Keras. 'ResNet50' is a pre-trained deep learning model for image classification that can be used as a feature extractor or fine-tuned for specific tasks.
7.numpy: NumPy is a fundamental package for scientific computing in Python. NumPy offers robust support for handling large, multi-dimensional arrays and matrices, accompanied by a comprehensive suite of mathematical functions tailored for array operations. NumPy arrays are commonly used to represent image data and model parameters in deep learning.
8.skimage.transform and sklearn.metrics: These modules provide functions for image transformation and metrics for evaluating machine learning models, respectively. Image transformation functions can be used for preprocessing images before feeding them into a deep learning model. Metrics such as confusion matrix and precision-recall-fscore support are used to evaluate the performance of classification models.
9.seaborn: Seaborn is a data visualization library based on matplotlib. It offers a user-friendly interface for generating visually appealing and insightful statistical graphics. Seaborn is often used to visualize the distribution of data and relationships between variables in deep learning tasks.
10.splitfolders: This utility is used for splitting a dataset into training, validation, and testing sets. It helps in organizing the data for training and evaluating deep learning models by automatically creating the required folder structure.

4.2.1 Advantages

Using image processing techniques with TensorFlow and Keras for kidney disease detection offers several advantages:

1. Early Detection: Image processing algorithms can detect kidney abnormalities at an early stage, allowing for timely medical intervention and potentially better outcomes for patients.

2. Accurate Classification: TensorFlow and Keras provide powerful tools for building accurate classification models. By training on a large dataset of kidney images labeled with normal, cyst, tumor, and stone classes, the model can learn to accurately classify new images, aiding in diagnosis.

3. Non-invasive Diagnosis: Image processing techniques offer a non-invasive way to diagnose kidney diseases. Patients can undergo imaging tests like CT scans or MRIs without the need for invasive procedures, reducing discomfort and risk.

4. Automation: Once trained, the model can automate the process of analyzing kidney images, freeing up valuable time for healthcare professionals. This can lead to faster diagnosis and treatment decisions.

5. Objective Analysis: Human interpretation of medical images can be subjective and prone to errors. Using image processing algorithms ensures a more objective analysis of kidney images, reducing the risk of misdiagnosis.

6. Scalability: TensorFlow and Keras are highly scalable frameworks, allowing the kidney disease detection model to be deployed across different healthcare facilities and integrated into existing medical systems.

7. Customization: Researchers and developers can customize the model architecture and fine-tune hyperparameters to improve performance on specific types of kidney abnormalities or to adapt to new datasets.

8. Data Mining and Insights: By analyzing a large dataset of kidney images, researchers can gain insights into the characteristics and patterns of different kidney diseases, potentially leading to new discoveries and treatment strategies.

9. Educational Tool: The model can serve as an educational tool for medical students and professionals, helping them learn about different types of kidney abnormalities and how they appear in imaging tests.

10. Cost-Effective: Automating the detection process with image processing techniques can potentially reduce healthcare costs by streamlining diagnosis and treatment planning.

4.2.2 Application

Detecting kidney diseases using image processing and machine learning techniques such as TensorFlow and Keras can have several practical applications in the medical field. Here are some potential applications:

1. Early Diagnosis: Early detection of kidney diseases such as cysts, tumors, and stones can lead to timely medical intervention and improved patient outcomes. By analyzing kidney images using deep learning models, abnormalities can be detected at an early stage, allowing for prompt treatment.

2. Automated Screening: Automated screening systems can assist radiologists in analyzing a large number of kidney images efficiently. Deep learning models can be trained to classify images into different classes (normal, cyst, tumor, stone) with high accuracy, reducing the workload on medical professionals and speeding up the diagnosis process.

3. Telemedicine: In regions with limited access to specialized healthcare services, telemedicine platforms can utilize image processing techniques to remotely assess kidney health. Patients can upload kidney images, which can then be analyzed by machine learning algorithms to detect abnormalities and provide preliminary assessments, enabling remote consultation with healthcare professionals.

4. Personalized Treatment Planning: By accurately classifying kidney images, healthcare providers can tailor treatment plans based on the specific type and severity of kidney disease. For example, treatment strategies for kidney tumors may differ from those for cysts or stones, and precise classification can help guide treatment decisions.

5. Research and Development: Image processing techniques combined with machine learning can aid researchers in studying patterns and characteristics of different kidney diseases. By analyzing large datasets of kidney images, researchers can gain insights into disease progression, risk factors, and treatment efficacy, ultimately contributing to the development of new diagnostic tools and therapies.

6. Education and Training: Medical students and professionals can benefit from interactive educational tools that utilize image processing and machine learning to simulate real-world scenarios of kidney disease diagnosis. These tools can provide hands-on experience in interpreting medical images and understanding the nuances

of different kidney pathologies. Overall, the application of image processing and machine learning techniques for kidney disease detection holds significant promise in improving diagnostic accuracy, facilitating early intervention, and enhancing patient care in the field of nephrology.

4.3 Making Website

4.3.1 Flask Framework

Flask is a micro web framework for Python, meaning it provides the tools and libraries to help you build web applications, but it doesn't enforce any dependencies or project layout. Here's a detailed explanation of Flask:

1.Micro Framework: Flask is often referred to as a "micro" framework because it aims to keep the core simple and extensible. This means that Flask provides only the essential tools needed for web development, such as routing, request handling, and response generation, but leaves other features (like database integration, authentication, etc.) to be added as needed through extensions.

2.Routing: One of the key features of Flask is its routing system. Routes are used to map URLs to Python functions, allowing you to define how your application responds to different requests. For example, you can use a route decorator to specify that a certain function should be called when a user visits a particular URL.

3.Request Handling: Flask provides a request object that contains information about the incoming request, such as the URL, form data, and request method (GET, POST, etc.). This allows you to access and process the request data in your application.

4.Response Generation: Similarly, Flask provides a response object that allows you to generate HTTP responses to send back to the client. This can include HTML content, JSON data, or any other type of response your application needs to send.

5.Template Rendering: Flask also includes a templating engine called Jinja2, which allows you to generate HTML dynamically in your application. This makes it easy to create web pages that can display dynamic content based on data from your application.

6.Extensions: While Flask itself is minimalistic, it has a large ecosystem of extensions that can be used to add additional functionality to your application. For example, there are extensions available for integrating with databases (SQLAlchemy), handling user authentication (Flask-Login), and creating RESTful APIs (Flask-RESTful).

7.Development Server: Flask includes a built-in development server that makes it easy to test your application locally during development. This server is not meant for production use, but it's great for getting started quickly and testing your application's functionality.
8.Deployment: When you're ready to deploy your Flask application to a production server, there are several options available. Flask applications can be deployed to traditional web servers like Apache or Nginx using WSGI (Web Server Gateway Interface), or you can use a platform-as-a-service (PaaS) provider like Heroku or PythonAnywhere. Overall, Flask is a flexible and lightweight framework that is great for building small to medium-sized web applications. It's easy to get started with and offers a lot of flexibility for developers.

4.4 Result

4.4.1 Confusion matrix

Confusion Matrix Theory A confusion matrix is a table that's used to estimate the performance of a bracket model. It summarizes the results of bracket by comparing prognosticated classes with true classes. In your case, with five classes(normal, excrescence, tubercle, gravestone, and no order), the confusion matrix will be a 5x5 matrix.

Actual Classes \ Predicted Classes	Normal	Tumor	Cyst	Stone	No Kidney
Normal	TN(NN)	FP(NT)	FP(NC)	FP(NS)	FP(NNK)
Tumor	FP(TN)	TN(TT)	FP(TC)	FP(TS)	FP(TNK)
Cyst	FP(CN)	FP(CT)	TN(CC)	FP(CS)	FP(CNK)
Stone	FP(SN)	FP(ST)	FP(SC)	TN(SS)	FP(SNK)
No Kidney	FP(NKN)	FP(NKT)	FP(NKC)	FP(NKS)	TN(NK)

Figure 4.3: Predicted Classes

Here's Each cell represents

1. TN(True Negative) The number of cases where the model rightly prognosticated the absence of the corresponding condition(true negative).

2. FP(False Positive) The number of cases where the model inaptly prognosticated the presence of the corresponding condition when it wasn't present(false positive).

3. FN(False Negative) The number of cases where the model inaptly prognosticated the absence of the corresponding condition when it was present(false negative).

4. TP(True Positive) The number of cases where the model rightly prognosticated the presence of the corresponding condition(true positive).

Metrics Derived from Confusion Matrix: Using the values from the confusion matrix, you can calculate various performance metrics:

1. Accuracy: (TN(NN) + TN(TT) + TN(CC) + TN(SS) + TN(NK)) / Total instances
2. Precision (for each class): TP / (TP + FP) for each class
3. Recall (for each class): TP / (TP + FN) for each class
5. F1-score (for each class): Harmonic mean of precision and recall for each class
6. Overall Precision, Recall, and F1-score: Macro-average or weighted-average of precision, recall, and F1-score across all classes
7. Specificity (for each class): TN / (TN + FP) for each class (applicable for binary classification)

These metrics provide insights into the performance of your classification model for each class and overall. By analyzing the confusion matrix and derived metrics, you can identify areas for improvement in your model and make adjustments to enhance its performance for diagnosing kidney diseases accurately, including the detection of cases where no kidney is present.

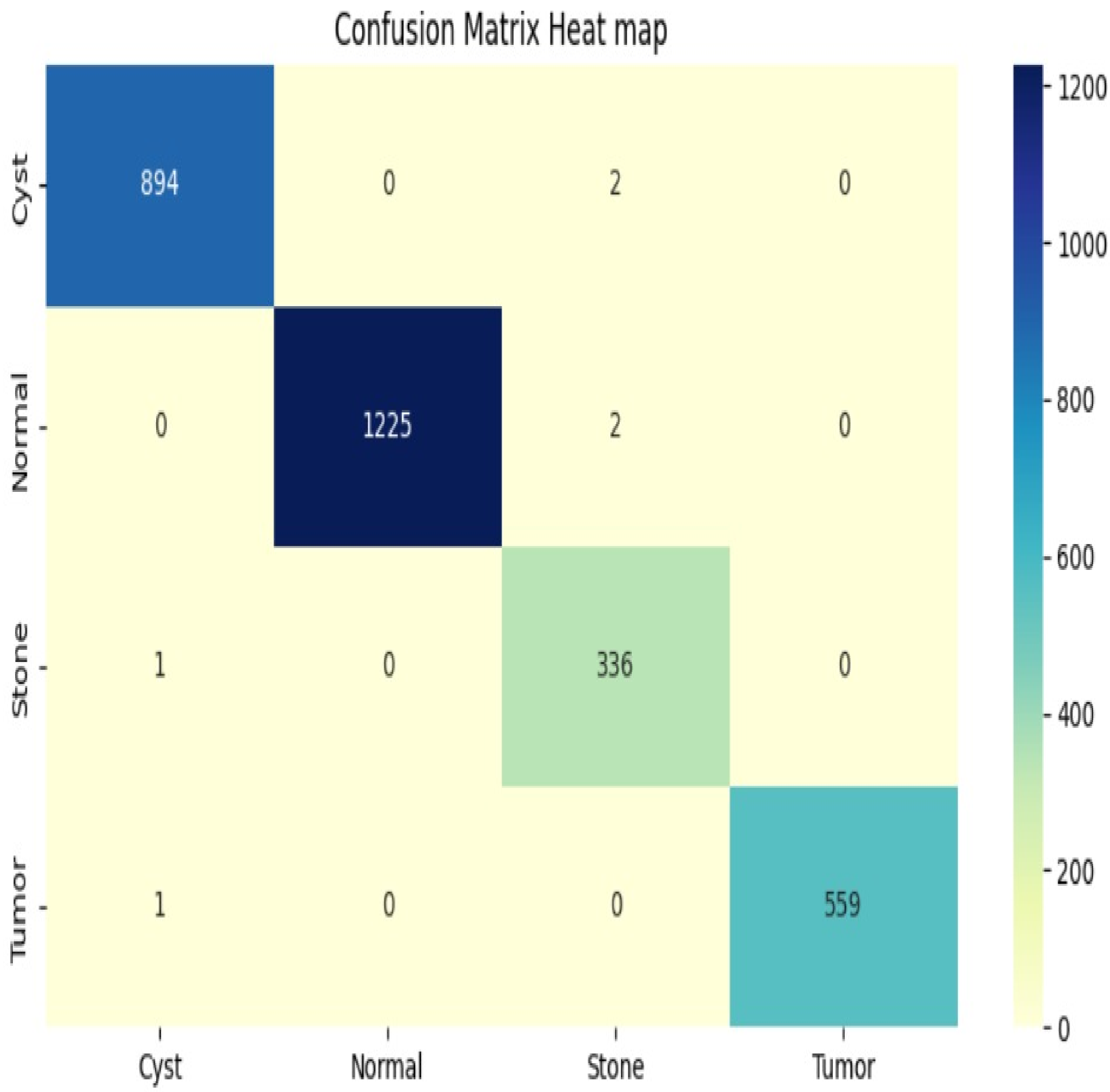


Figure 4.4: Confusion matrix

4.4.2 User Interface

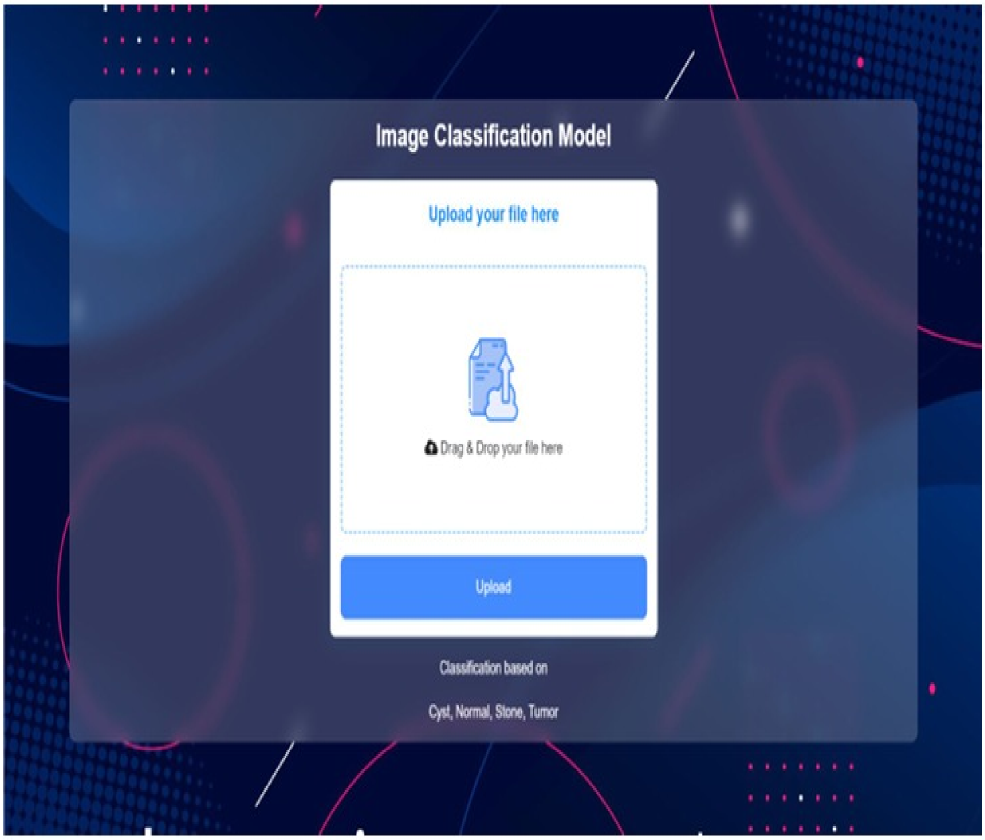


Figure 4.5: Uploading the image

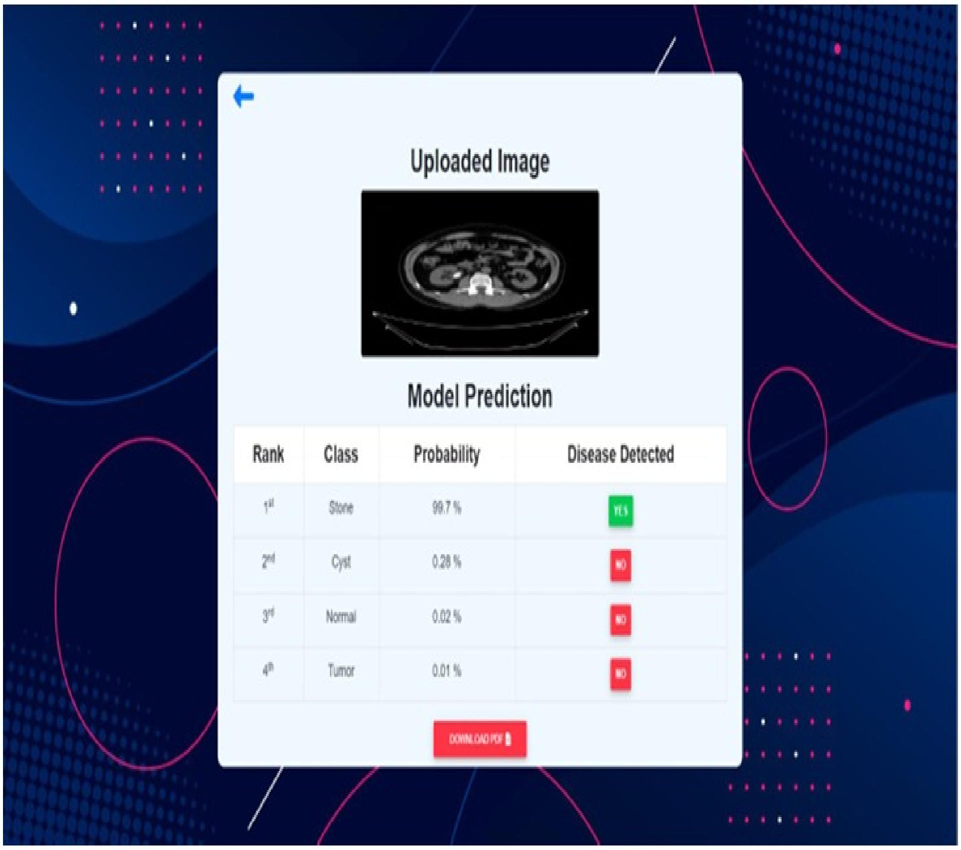


Figure 4.6: Stone Accuracy

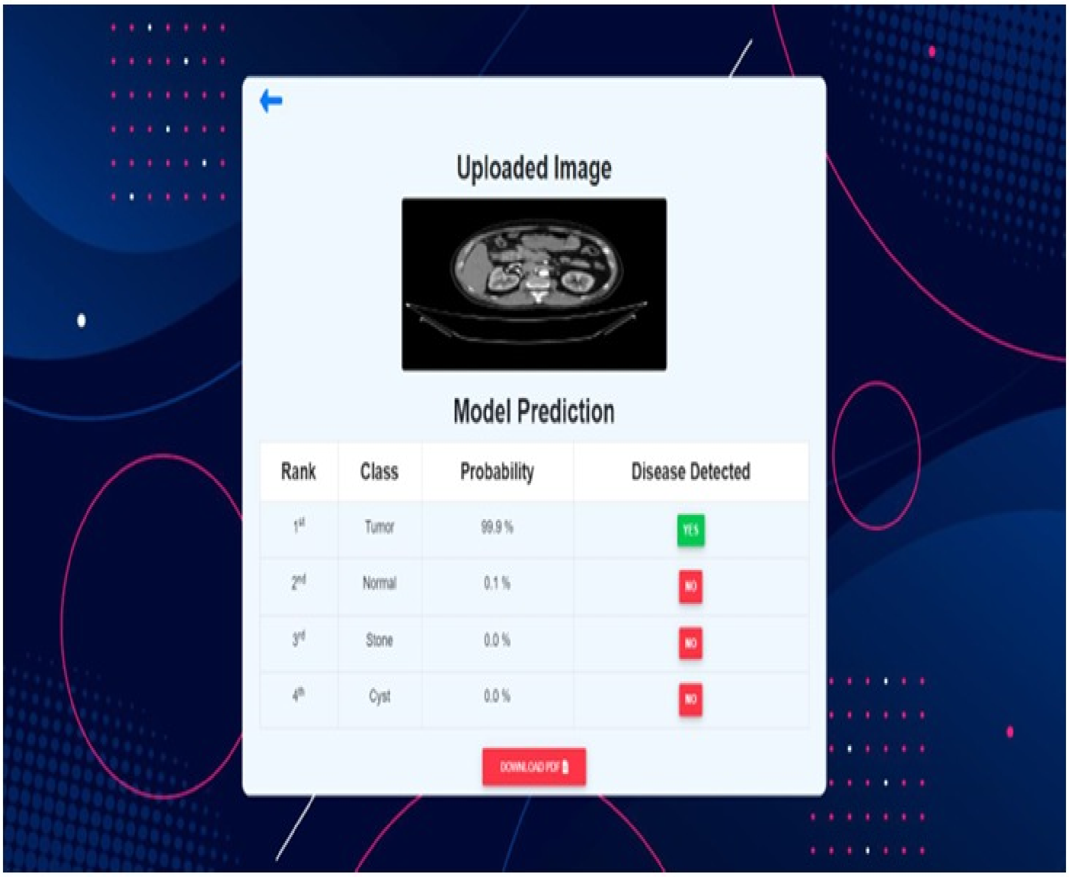


Figure 4.7: Tumor Accuracy

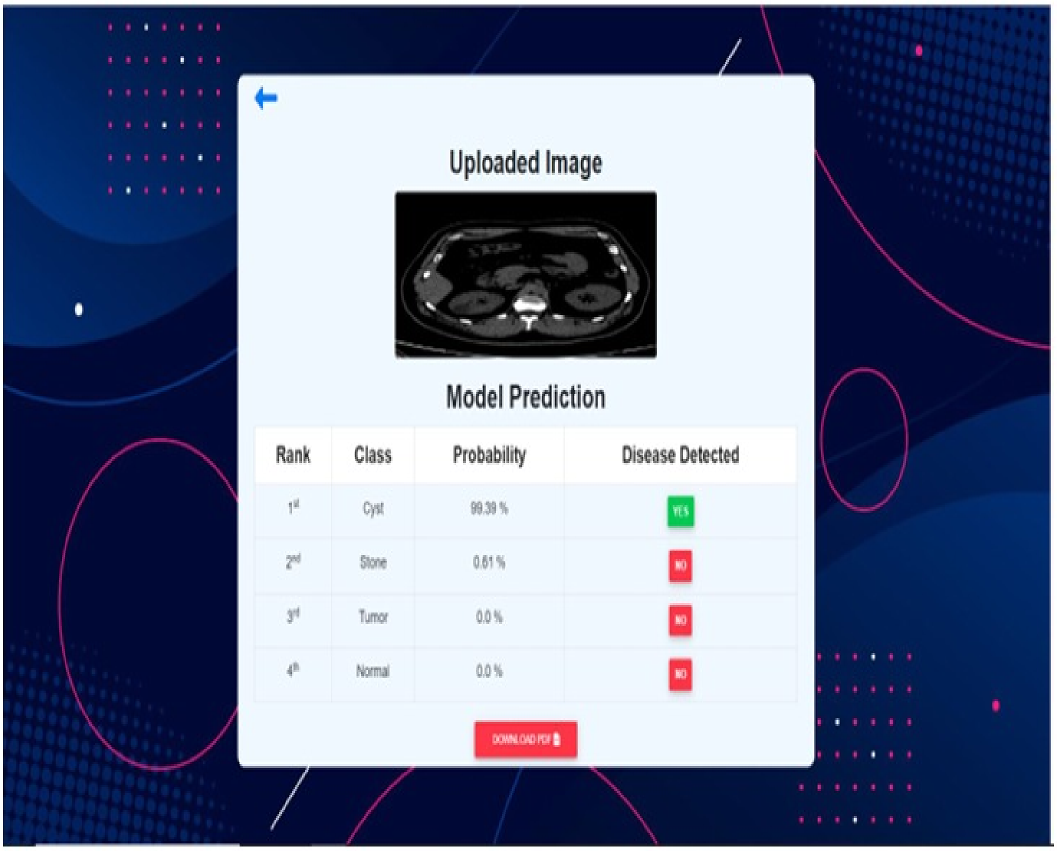


Figure 4.8: Cyst Accuracy

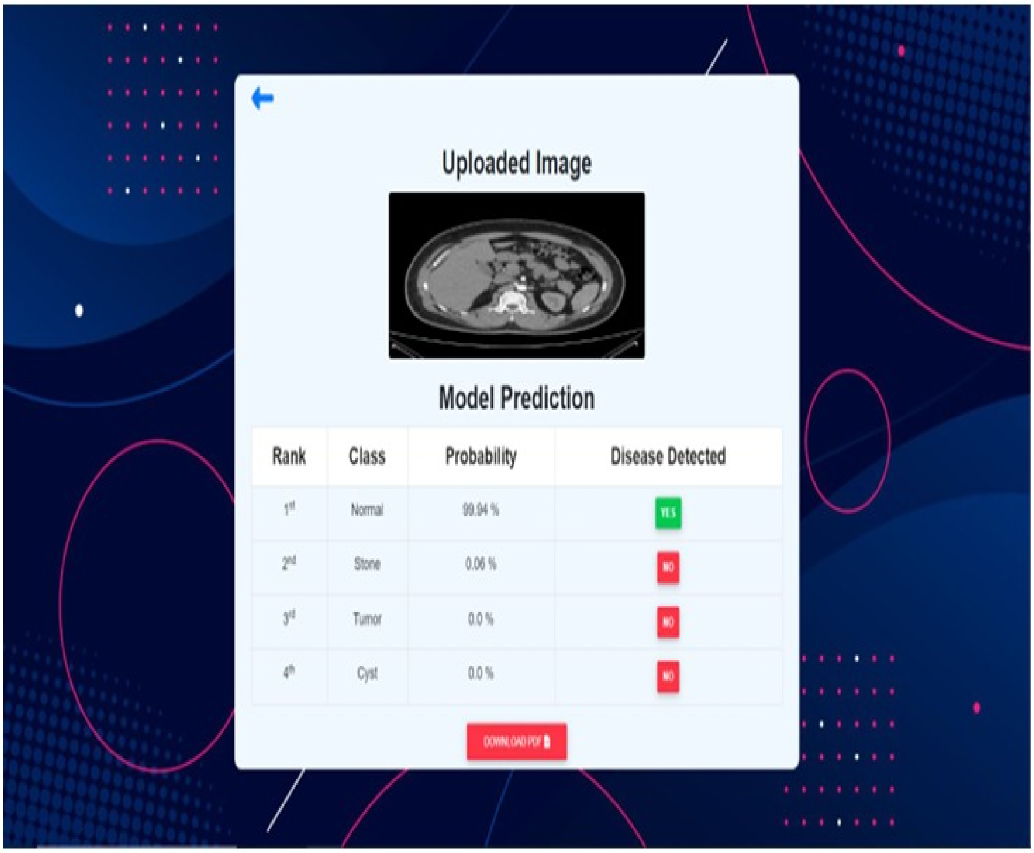


Figure 4.9: Normal Accuracy

Chapter 5

System Requirement Analysis

5.1 Software Requirements

In Software requirements, we need all that software that provides us with better functionality of the project without creating problems or bugs. The minimum software that is needed in this project is as follows:

5.1.1 Python

Python is an interpreted, object- acquainted, high- position programming language with dynamic semantics developed by Guido van Rossum. It was originally released in 1991. Python, designed to be both easy and enjoyable, pays homage to the British comedy group Monty Python with its name. Python has a character as a beginner-friendly language, replacing Java as the most considerably used introductory language because it handles much of the complexity for the user, allowing beginners to concentrate on fully grasping programming generalities rather than minute details.

Python is widely used for server-side web development, software development, mathematics, system scripting, and is renowned for its role in Rapid Application Development. It is also popular as a scripting or glue language.tie being factors because of its high- position, erected- in data structures, dynamic typing, and dynamic list. Program conservation costs are reduced with Python due to the easily learned syntax and emphasis on readability. Additionally, Python's support for modules and packages enables the creation of modular programs and the practice of good software engineering principles.Python is an open source community language, so numerous independent programmers are continually erecting libraries and functionality for it.

Python Use Cases:

- Creating web operations on a garçon
- structure workflows that can be used in convergence with software
- combining to database systems
- Reading and modifying lines
- Performing complex mathematics
- Processing big data
- Fast prototyping
- Developing product-ready software

Features and Benefits of Python:

- Compatible with a variety of platforms including Windows, Mac, Linux, Raspberry Pi, and others
- Uses a simple syntax analogous to the English language that lets formulators use lower lines than other programming languages
- Operates on an guru system that allows law to be executed directly, presto-shadowing prototyping
- Can be handled in a procedural, object- acquainted, or functional way

5.1.2 Visual Studio

Visual Studio is a robust integrated development environment (IDE) developed by Microsoft. It provides a range of features to support the development of various types of applications, including web development. Here's a detailed explanation of how you might have used Visual Studio for your project:

1.Code Editor: Visual Studio offers a robust code editor with features like syntax highlighting, IntelliSense (code completion), and code formatting, which can help you write HTML and CSS more efficiently.

2.Project Management: Visual Studio helps you manage your website project by organizing files, folders, and resources in a structured manner. You can easily add, remove, and edit files within the project.

3.Debugging: The IDE includes powerful debugging tools that allow you to identify and fix issues in your HTML, CSS, and JavaScript code. You can set breakpoints, inspect variables, and step through code to understand its behavior.

4.Integrated Terminal: Visual Studio includes an integrated terminal, which you can use to run commands, such as starting a local development server or installing dependencies using npm or other package managers.

5.Version Control: Visual Studio has built-in support for version control systems like Git. You can easily commit changes, create branches, and merge code directly from the IDE.

6.Extensions: Visual Studio supports a wide range of extensions that can enhance its functionality. For web development, you might use extensions for frameworks like Bootstrap or libraries like jQuery, which can provide additional features and tools specific to those technologies.

7.Publishing: Once your website is ready, Visual Studio provides tools to publish it to a web server. You can configure deployment settings, such as target location and deployment method, directly from the IDE.

Overall, Visual Studio provides a comprehensive set of tools and features that can greatly simplify the process of developing, debugging, and deploying websites using HTML and CSS.

5.2 Hardware Requirements

When addressing demand, we require all the necessary elements that provide us with a platform for designing. The minimal requirements for this design are as follows:

CPU Configuration	Intel® core i5
Processor	1.80GHz
RAM	8.00 GB
Disk Space– 64 Bit	2GB
Disk Space– 64 Bit	3GB

Figure 5.1: Hardware Requirements

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

According to the findings of the study, the decision tree approach and logistic retrogression can be used to prognosticate habitual order complaint more directly. According to the study, their perfection was96.25 percent, and their delicacy was 97 percent. Compared to previous exploration, the delicacy percent of the models used in this disquisition is vastly advanced, indicating that the models used in this study are more dependable than those used in former studies. When cross confirmation measures are used in the vaticination of habitual order complaint, the LR system outperforms the other processes. unborn exploration may make on this work by developing a web operation that incorporates these algorithms and using a bigger dataset than the one employed in this study. This will prop in the achievement of bettered issues as well as the delicacy and effectiveness with which healthcare interpreters can anticipate order issues.

This will enhance the responsibility of the frame as well as the frame's donation. The stopgap is that it would encourage people to seek early treatment for habitual renal complaint and to make advancements in their lives. Early opinion and treatment of habitual order complaint are possible, but as the con dition worsens, recovery is unattainable. The use of dialysis or renal relief remedy is eventually needed. To put it another way, it's critical to identify and manage habitual renal illness as soon as possible. Using information similar order size and internal echo housekeeper acteristics, ultrasound is used to examine information on the degree of inflammation when diagnosing order cancer, seditious conditions, nodular conditions, habitual renal complaint, etc

6.2 Future Scope

The future scope of kidney disease detection using image processing, TensorFlow, and Keras to classify normal, cyst, tumor, and stone classes is quite promising. Here are several potential avenues for further exploration and development:

1. Enhanced Image Processing Techniques: Further advancements in image processing algorithms can improve the accuracy of kidney disease detection. Techniques such as image enhancement, noise reduction, and feature extraction can be explored to better highlight relevant features in kidney images.

2. Deep Learning Architectures: Experimenting with various deep learning architectures beyond the basic convolutional neural networks (CNNs) can lead to improved performance. Architectures like recurrent neural networks (RNNs), attention mechanisms, and transformers may offer better understanding and classification of complex kidney images.

3. Transfer Learning and Pretrained Models: Leveraging transfer learning with pretrained models can expedite the training process and improve the performance, especially when dealing with limited labeled data. Models pretrained on large medical imaging datasets or related domains can be fine-tuned for kidney disease detection.

4. Multi-Modal Fusion: Integrating multiple modalities such as CT scans, MRI images, and ultrasound scans can provide a more comprehensive understanding of kidney health. Fusion techniques that combine information from different modalities can potentially improve the accuracy and robustness of the classification system.

5. Data Augmentation and Synthetic Data Generation: Generating synthetic data or augmenting existing datasets can help address the challenge of limited labeled data. Techniques such as geometric transformations, adding noise, and generative adversarial networks (GANs) can be employed to create diverse training samples.

6. Explainable AI and Interpretability: Developing models with explainable AI capabilities can enhance the interpretability of classification decisions. Techniques such as attention maps, saliency maps, and gradient-based methods can provide insights into which regions of the kidney images are most influential for

classification.

7. Clinical Integration and Validation: Collaborating with healthcare professionals and clinicians for real-world validation and integration of the developed system is essential. Clinical validation studies can assess the performance, reliability, and usability of the system in real clinical settings, ultimately leading to its adoption in medical practice.

8. Scalability and Deployment: Designing the system to be scalable and deployable in diverse healthcare settings is crucial for widespread adoption. Considerations such as computational efficiency, compatibility with different hardware platforms, and compliance with regulatory standards need to be addressed for successful deployment. By exploring these avenues, researchers and developers can further advance the field of kidney disease detection using image processing and deep learning, ultimately leading to improved diagnosis, treatment, and management of kidney-related disorders.

Appendix A

Monthly Progress Evaluation Report

Project Title: Kidney Disease Detection using Deep learning
Group Members:

- Sharvaree Bamane
- Jyotsna Chitte
- Sonal Ghuge

Month of Evaluation: [Enter Month 1 dates: 1 JAN - 31 JAN]

Progress Report

1. Individual Contribution

- **Sonal Ghuge:** Research paper studies and Developing an environment and importing required libraries.
- **Jyotsna Chitte:** Research paper studies and Basic code implementation.

- **Sharvaree Bamane:** Research paper studies and Designing basic architecture for the project.

2. Update of Proposal

- **Proposal Background:** The project proposal aims to develop a system for predictive analytics using Kidney disease early detection. The system will enable users, particularly we do the prediction of each find dataset and study about dataset
- **Progress Clarification:** The purpose of this progress report is to provide an update on the project's development, including completed tasks, ongoing work, and future plans.

3. Explanation of Progress

1. **Work Completed:**
    - Task A: Taken Details of dataset.
    - Task B: Import and understand our dataset and perform EDA analysis
2. **Future Work:**
    - Task A: Optimizing the code architecture.
    - Task B: Working on prediction of Kidney dieases.

4. Conclusion

In this month we did research on our projects,gained necessary knowledge needed for the project. Also we did environment set-up and worked on the architecture of the project.We are working on optimizing the current code.

Month of Evaluation: [Enter Month 2 dates: 1 FEB to 29 FEB]

Progress Report

1. Individual Contribution

- **Jyotsna Chitte:** Kidney diseases prediction code
- **Sonal Ghuge:** Give each parameters analyze
- **Sharvaree Bamane:** Kidney diseases prediction documentations

2. Update of Proposal

- **Proposal Background:** The project proposal entails the development of Kidney Disease Detection using Deep learning, along with predictive analytics in cardiology. The aim is to provide an accessible means of interacting with dieasescardiovascular health plays pivotal roles in developing various Kidney conditions.
- **Progress Clarification:** The completed tasks include prediction programming and documentation of the Kidney diseases (Task A), prediction of programming completed(Task B). Future work involves To make website of Kidney dieases prediction identity the risk of patients

3. Explanation of Progress

1. **Work Completed:**
   - Task A: prediction in python programming and documentation of Kidney diseases
   - Task B: Analysis of coronary Artery of Kidney diseases predicted
2. **Future Work:**

- Task A: Make a website with User and a Upload Image page
- Task B: Then make a website to check patients have how much risk of Kidney diseases

4. Conclusion

Optimized and completed Prediction of Kidney diseases and some part of website.

Month of Evaluation: [Enter Month 3 dates: (1 MARCH to 31 MARCH)]

Progress Report

1. Individual Contribution

- **Sharvaree Bamane:** Integration of website Kidney dieases
- **Sonal Ghuge:** Integration of prediction and website, documentation of the project.
- **Jyotsna Chitte:** Development prediction of Kidney diseases.

2. Update of Proposal

- **Proposal Background:** Our project focuses on the development of a Prediction of coronary artery diseases, leveraging Python programming language to make a prediction using four parameters Cyst, Normal, Tumor, Stone. Then make a website and analyse patient risk high, moderate, and low.
- **Progress Clarification:**This progress report encompasses the evaluation period from 1 March to 31 March. It provides an overview of the advance-

ments made in integrating the Prediction of cardiology detection of Kidney diseases, as well as the documentation of the project.

3. Explanation of Progress

1. **Work Completed:**

    - Task A: Integration of the project including the Kidney diseases website.

    - Task B: Complete documentation of the entire project, encompassing all Prediction and website

4. Conclusion

During this evaluation period, significant progress was made in integrating the project components and ensuring accuracy and user interface enhancements. Additionally, the comprehensive documentation of the project provides a detailed overview of its implementation, Prediction, and technical aspects.

Appendix B

Brief Biodata of each student

B.1 SHARVAREE BAMANE

Branch-Data Science .

Email id-sharvaree59@gmail.com

Area of specialization- python ,Excel ,Data analyst, Visualization, Machine Learning, Basic Deep Learning. , Data Science and Analytics

Skills-Python , Tableau , Power BI , Analytical Tool: Jupyter Notebook

Experience-AI/ML internship at Internpe

Certifications MS Excel, CCC

Internship Experience-AI/ML internship at Internpe

B.2 Jyotsna Chitte

Branch: Data Science .

Email id: joshuchitte003@gmail.com

Area of specialization: python , SQL, Excel ,Data analyst, Visualization, Machine Learning, Basic Deep Learning.

Skills: Python , Tableau , Power BI , Visual Studio

Experience: AI/ML internship at Internpe

Interests: Creativity, Problem Solving

Internship Experience: AI/ML internship at Internpe

B.3 SONAL GHUGE

Branch: Data Science .

Email: sonalghuge2001@gmail.com

Area of specialization: Machine learning,Nural Network Deep Learning, Data Analyst

Skills: C++, C, python, HTML,CSS,Tableau,PowerBI, Machine learning

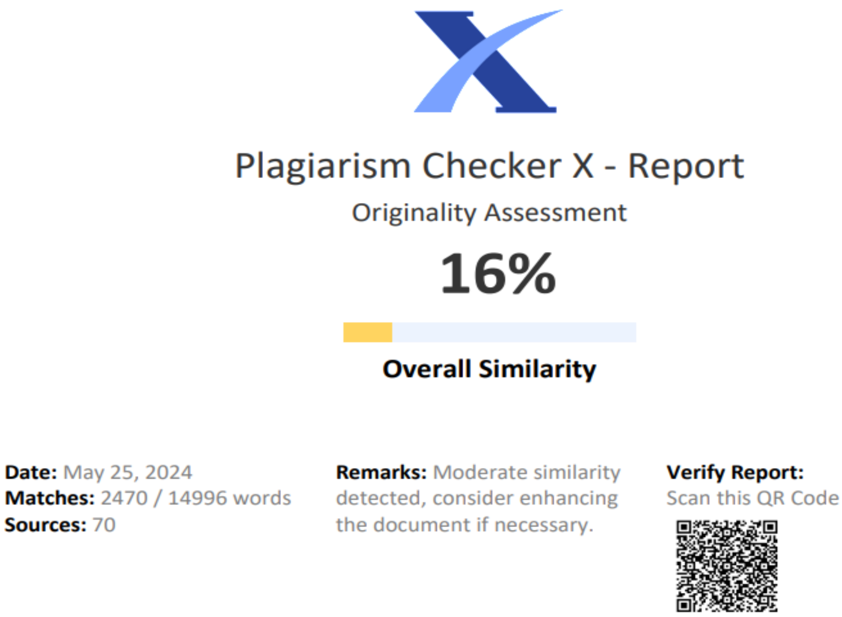
Experience: Branding Catalyst PVT.LTD

Interests: Innovation, Problem solving.

Internship: Branding Catalyst PVT.LTD
Position of Responsibility : Core Member at WIE on the Possition Event and External Affiar Directed

Appendix C

Plagiarism Report



Plagiarism Checker X - Report

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16%

Overall Similarity

Date: May 25, 2024
Matches: 2470 / 14996 words
Sources: 70

Remarks: Moderate similarity detected, consider enhancing the document if necessary.

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Figure C.1: plagiarism report

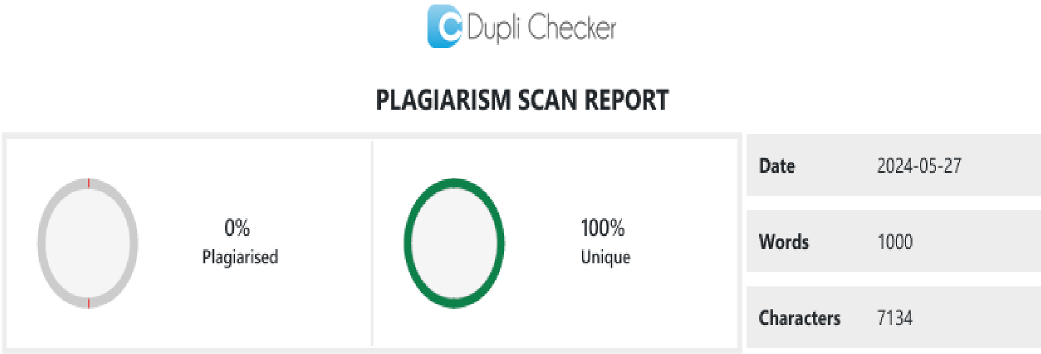

Figure C.2: Publish Paper plagiarism report

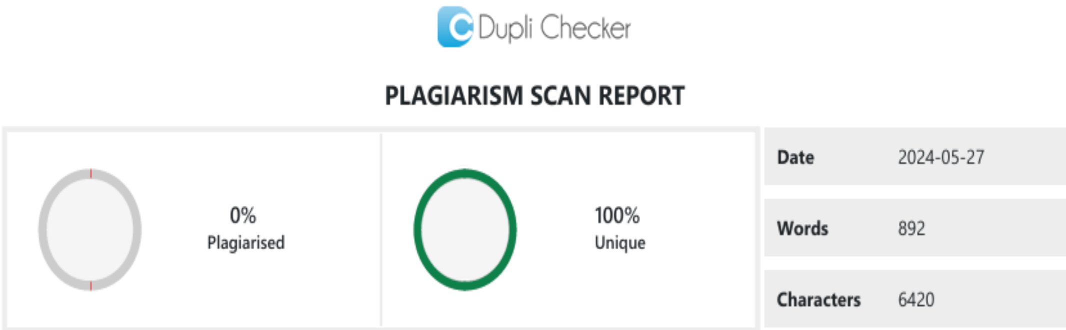

Figure C.3: Publish Paper plagiarism report

Appendix D

Research paper based on project

editor@irjmets.com
to me

Fri, Apr 12, 9:56 AM

Subject - **Paper Accepted successfully.**

Dear Author/Research Scholar,

Congratulation

Your research paper entitled "**Kidney Disease Detection using Deep learning**" is accepted for publish in International Research Journal of Modernization in Engineering Technology & Science (IRJMETS) – Volume 6 Issue 4, April 2024.

PAPER ID: IRJMETS60400088048

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KIDNEY DISEASE DETECTION USING DEEP LEARNING

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ABSTRACT

Kidney diseases pose a significant health threat globally, often leading to severe complications if not diagnosed and treated early. In recent years, advancements in medical imaging and machine learning techniques have shown promising results in the early detection and classification of kidney abnormalities. This study proposes a novel approach utilizing image processing techniques implemented in TensorFlow and Keras to accurately detect and classify kidney diseases into four classes: normal, cyst, tumor, and stone. The proposed system begins with the acquisition of kidney images through various medical imaging modalities such as ultrasound, xray. These images are pre-processed to enhance their quality and standardize features for improved analysis. Convolutional Neural Networks (CNN), a powerful class of deep learning models, are then employed to automatically extract discriminative features from the pre- processed images. TensorFlow and Keras frameworks are utilizedfor the development and training of the CNN models.

Keywords: Kidney Disease Detection Using Deep Learning, Scanned Images, Image Processing, Confusion Matrix, Predict Disease, Etc.

I. INTRODUCTION

Kidney disease is a major global health issue, affecting mil- lions and causing significant illness and death. Detecting and classifying kidney problems accurately and quickly is crucial for proper treatment. Recently, combining image processing with deep learning tools like TensorFlow and Keras has shown promise in improving the diagnosis of kidney diseases. This approach involves using these tools to analyze images and identify various kidney abnormalities, including cysts, Normal, tumors, and stones. Kidney diseases can vary widely, fromharmless cysts to dangerous tumors. While traditional methods like ultrasound and MRI provide useful images for doctors, interpreting these images can be slow and subjective. Deep learning algorithms, like those in TensorFlow and Keras, are adept at finding complex patterns in large datasets. By using these algorithms, researchers can train computers to recognize different kidney abnormalities in images more efficiently. To use this approach, researchers first gather a diverse set ofkidney images, including normal and abnormal cases, and thenprocess them to improve their quality. They then design a spe-cialized neural network called a convolutional neural network (CNN) using TensorFlow and Keras. CNNs are excellent at automatically extracting features from images, making them ideal for this task. The trained model is then tested on separate datasets to evaluate its accuracy and performance, potentially leading to quicker and more accurate diagnoses for kidney diseases.

II. LITERATURE REVIEW

1. Hadjiyski suggests that creating a classifier to separate between normal and cancerous order images can prop in relating order cancer automatically. They also probe how the scale of cropped images affects the delicacy of deep literacy neural networks(DLNN).The design aims to develop a DLNN- grounded system to directly estimate the stage of order cancer. They used the TensorFlow frame and the Inception V3 deep literacy network structure.
2. Subhanki B from Sri Eshwar College of Engineering's Department of Computer Science and Engineering highlightedthe significance of machine learning algorithms in diagnos-ing chronic kidney disease (CKD) in 2021. They suggested that applying these algorithms to CKD diagnosis could be highly effective. CKD often shows no initial symptoms, but later symptoms can include swelling in the legs, fatigue, nausea, loss of appetite, and confusion. The causes of CKD include hypertension, diabetes, polycystic kidney disease, and glomerulonephritis, with a family history of chronic renal disease being a risk factor.

3. As well as how weka and machine literacy approaches may be used to identify it. The threat of cardiovascular complaint and end- stage renal complaint is increased by ha- bitual order complaint. When habitual renal complaint reachesan advanced position, the body may begin to accumulate electrolytes and waste. Multilayer perceptronis a general word for any feed-forward ANN that's used ambiguously and fre- quently. Machines are able of both illness discovery and complaint vaticination. The delicacy, ROC, perfection, recall, and f measure have been determined in this study using a variety of machine literacy classifiers.
4. A study focused on classifying chronic kidney disease (CKD) using various algorithms found that CKD is a seri- ous global health issue leading to adverse consequences and millions of deaths annually due to inadequate treatment. The team evaluated several machine learning (ML) algorithms andfound that logistic regression had the highest accuracy and recall, while decision trees had the best precision. Detecting CKD early and accurately can significantly improve patient outcomes by prolonging life and increasing the chances of successful treatment.

III. METHODOLOGY

Detecting order conditions through image processing using TensorFlow and Keras involves several way preprocessing the images, erecting a deep literacy model, training it, and also assessing its performance. The first step is to preprocess the images. This involves tasks like resizing, normalization, and addition to enhance the quality and variability of the dataset. also, the dataset is resolve into training, confirmation, and testing sets. Next, a deep literacy model is erected using TensorFlow and Keras. Convolutional Neural Networks(CNN) are generally used for image bracket tasks due to their capability to automatically learn applicable features from images. The model armature generally consists of multiple convolutional layers followedby pooling layers to prize features and reduce dimensionality, and also completely connected layers for bracket.

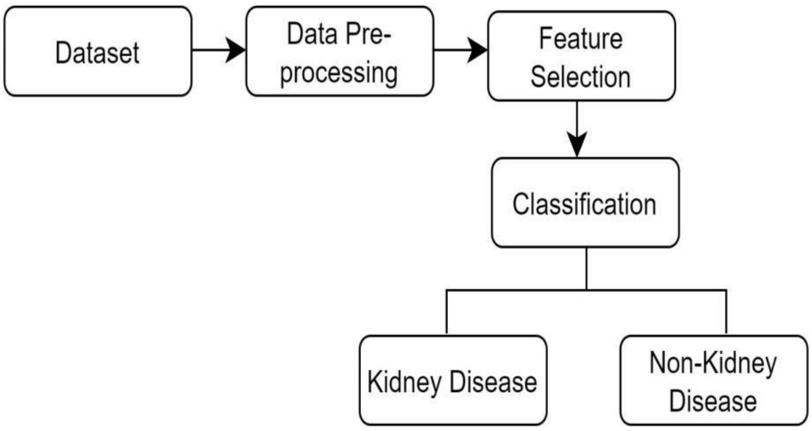

Fig 1: Flowchart

IV. PROPOSED SYSTEM

Kidney disease detection is crucial for early diagnosis and effective treatment. This proposed methodology utilizes image processing techniques implemented with TensorFlow and Keras to classify kidney images into four classes: normal, cyst, tumor, and stone.

1. Data Acquisition: A dataset containing a variety of kid-ney images representing different classes (normal, cyst, tumor, stone) is collected. These images can be obtained from medical databases or through collaboration with healthcare institutions. [2]Preprocessing: Image preprocessing techniques are ap- plied to enhance image quality and remove noise. This may include resizing, normalization, and noise reduction to ensureuniformity and improve the effectiveness of subsequent processing steps.
2. Feature Extraction: Features relevant to kidney disease diagnosis are extracted from preprocessed images. These fea- tures could include texture, shape, and intensity characteristicsthat distinguish between different classes of kidney abnormal- ities.
3. Model Development: A convolutional neural network(CNN) architecture is designed using TensorFlow and

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imple- mented with Keras. The CNN architecture is trained on the extracted features using a labeled dataset. Transfer learning techniques, such as fine-tuning pre-trained models like VGG or ResNet, can also be employed to improve performance, especially with limited data.

4. Model Training and Validation: The dataset is split into training, validation, and testing sets. The CNN model is trained on the training data and validated on the validation set to tune hyperparameters and prevent overfitting.
5. Evaluation: The trained model's performance is evaluated using the testing dataset to assess its accuracy, precision, recall, and F1-score. Confusion matrices and may also be analyzedto understand the model's behavior across different classes.
6. Deployment: Once the model demonstrates satisfactory performance, it can be deployed for real-world kidney disease detection applications. This could involve integration into medical imaging systems or development of a standalone application for healthcare professionals.

By employing this methodology, accurate and efficient kidney disease detection can be achieved, enabling timelyintervention and improved patient outcomes. Additionally, the use of TensorFlow and Keras provides a flexible and scalable framework for developing robust image classification models.

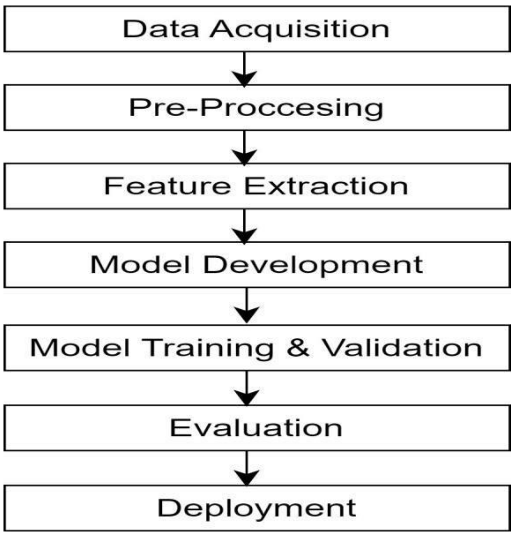

Fig 2: Proposed system.

V. CNN ARCHITECTURE

A Convolutional Neural Network(CNN) is a type of artificial neural network designed to reuse and dissect visual data, similar as images or vids. It's inspired by the structure and function of the mortal brain's visual cortex, whichis responsible for recycling visual information. Then is a brief explanation of the crucial factors of a CNN. Input Layer: This is where the raw data(e.g., an image) is fed into the network. Each data point(e.g., a pixel in an image)is represented as a numerical value. Convolutional Layers: These layers apply complication operations to the input data. A complication operation involves sliding a small matrix(called a sludge or kernel) over the input data to prize features. Each sludge detects specific patterns or features, similar as edges or textures, in the input data.Activation Function: After the complication operation, an activation function(similar as ReLU) is applied to introducenon-linearity into the network. This helps the network learn more complex patterns in the data.Pooling Layers: Pooling layers reduce the spatial confines of the input data by downsampling. Common pooling operations include maximum pooling(opting the maximum value from a group of values) and average pooling(calculating the average value from a group of values). Pooling helps reduce calculation and control overfitting. Completely Connected Layers: Also known as thick layers, these layers connect every neuron in one subcaste to every neuron in the coming subcaste. Completely connected layers are generally used towards the end of the network to collude the uprooted features to the affair classes(e.g., object orders in an image).Overall, CNNs exceed at learning spatial scales of features in data, making them well- suited for tasks like image recognition, object discovery, and image segmentation.

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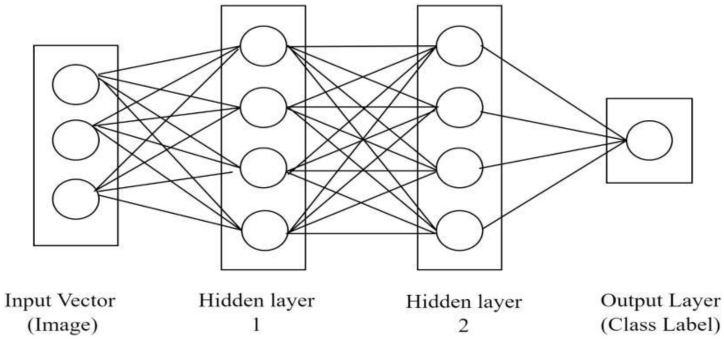

Fig 3: CNN Architecture.

VI. DATASET DISTRIBUTION

After building the model, it is trained on the preprocessed dataset using the training set. During training, the model adjusts its parameters using an optimization algorithm (e.g.,Adam) to minimize the classification error. The performance of the model is monitored using the validation set to avoid overfitting.Once training is complete, the model is evaluated using the testing set to assess its performance on unseen data. Evaluation metrics such as accuracy, precision, recall, and F1-score are computed to measure the model's effectiveness in classifying kidney images into normal, cyst, tumor, and stone classes.

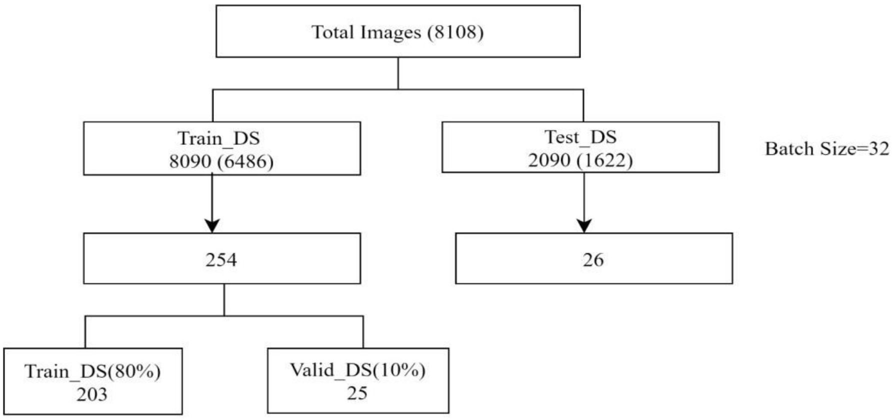

Fig 4: Dataset Distribution.

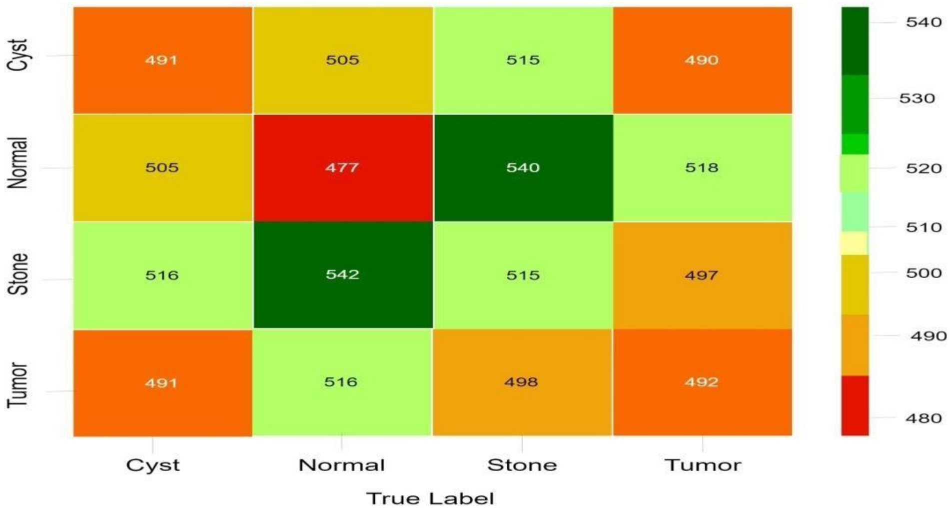

Fig 5: Confusion matrix.

VII. DEPLOYMENT

Finally, the trained model can be deployed in real-world applications for kidney disease detection. This could involve integrating it into medical imaging systems to assist radi-ologists in diagnosing kidney diseases more accurately and efficiently. In summary, kidney disease detection using image processing with TensorFlow and Keras involves preprocessing the images, building and training a deep learning model, evaluating its performance, and deploying it for real-world use,potentially improving the diagnosis and treatment of kidney diseases.

VIII. CONCLUSION

In implementing kidney disease detection using image processing with TensorFlow and Keras, several key conclusions can be drawn. Firstly, the model's accuracy in classifyingkidney images into normal, cyst, tumor, and stone classes is critical for accurate diagnosis. High accuracy indicates the model's effectiveness in distinguishing between these classes, which is vital for accurate diagnosis and treatment planning. Secondly, metrics like precision, recall, and F1-score provide important insights into the model's ability to correctly identifyinstances of each class while minimizing false positives and false negatives. These metrics help evaluate the model's overallperformance and effectiveness in detecting kidney abnormal- ities. Additionally, the model's robustness across different datasets and conditions is essential for its reliability in real- world applications.

IX. FUTURE SCOPE

The future scope of kidney disease detection using image processing, TensorFlow, and Keras is promising, with several avenues for advancement. Enhanced image processing tech- niques can improve feature extraction and noise reduction, leading to better classification accuracy. Experimentation with deep learning architectures beyond CNNs, such as RNNs and transformers, can enhance understanding of complex kidney images. Transfer learning with pretrained models can expedite training and improve performance, particularly with limited labeled data. Multi-modal fusion, including ultrasound scans, can provide a more comprehensive view of kidney health. Dataaugmentation and synthetic data generation techniques canaddress the challenge of limited labeled data. Explainable AI techniques can enhance the interpretability of classification de-cisions, aiding clinicians in understanding model predictions. Clinical integration and validation studies are essential for real-world adoption and validation of the developed system. Scalability and deployment considerations, such as computa- tional efficiency and regulatory compliance, are crucial for widespread adoption in healthcare settings. By exploring these avenues, researchers and developers can advance kidney dis- ease detection, ultimately improving diagnosis and treatment outcomes.

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Jyotsna Chitte

Sonal Ghuge