Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, No. 3, May : 2023

DETECTION OF CHRONIC KIDNEYBASED ON MACHINE LEARNING

S. Priya , Assistant Professor, Department of Information Technology, SNS College of Engineering Coimbatore, India.
Dr.P .Sumathi , HOD, Department of Information Technology, SNS College of Engineering Coimbatore, India.
R.Ushabala, S. Jeyashri , A. Rachel Fabiana , K.Karthikeyan, Student, Department of Information Technology, SNS College of Engineering Coimbatore, India.

ABSTRACT

Renal turmoil otherwise called chronic kidney disease (CKD) has been a very important field of study for a long while now. Early detection and diagnosis are mandatory for adequate therapy and prognostic improvement. Diagnosis of CKD requires a lot of tests and it's not a straightforward or easy process. Recent advancements in machine learning (ML) based disease classification have attracted researchers to investigate various health data. The aim of this project is to automate the kidney disease detection process of CKD using Lab Test and CT images by employing a deep learning (DL) model. Symptomatic Chronic Kidney Disease Prediction Model that employed BiLSTM algorithms to identify the presentation features predicting CKD disease diagnoses and DCNN algorithms were applied based on artificial intelligence by extracting and evaluating features using for different classes from pre-processed and fitted CKD datasets. Type of Kidney Disease Decision making is carried out in two stages: 1. Feature extraction 2. Image classification. The feature extraction is done using the **Gray Level Co-occurrence Matrix** and the image classification is done using **Convolutional Neural Network (CNN).** The MR images are classified into4 classes - Normal, Tumour, Cyst, Stone. In this project, we have measured accuracy, precision, recall, and calculated the loss and validation loss in prediction. The model outperforms traditional data classification techniques by providing superior predictive ability. Subsequently, the study proposed the integration of best performing DL models in the IoMT. This proposal will assist predictive analytics to advance CKD prediction by using deep learning more efficiently and effectively.

Keywords: ML, Kidney imaging, ultrasound, MRI scans, gray level co-occurrence Matrix, Convolutional Neural Network.

I.INTRODUCTION

A pair of bean-shaped organs, the kidneys are each roughly the size of a fist. They are shielded by the lower rib cage and joined to the upper back wall of the abdomen. Just left and right of the spine, respectively, are the two kidneys. Each kidney is topped by a little gland known as an adrenal gland. Fat and Gerota's fascia, a thin, fibrous layer, surround each kidney and adrenal gland. The primary function of the kidneys is to filter blood entering from the renal arteries to eliminate extra water, salt, and waste materials. These compounds cause urine to form. The renal pelvis, a region in the core of each kidney, is where urine gathers before leaving the kidneys. Approximately 10% of the world's population currently suffers from chronic renal disease, which claims the lives of millions of people each year and necessitates the use of dialysis for hundreds of thousands of others. Changes in the kidney's structure and operation that have been going on for longer than three months are referred to as chronic kidney disease. However, one of them is a benign structural abnormality called kidney cysts. Renal cysts, kidney tumours, and kidney stones all grow slowly and have no immediate effects on patients. The gastrointestinal system will, however, get compressed as the stones, masses, or cysts grow larger. As A result, the patient's stomach and intestines lose capacity and experience constant fullness. Many other people also experience symptoms. Simply put, a shallow neural network with multiple hidden layers is a deep neural network. In the buried layer, there are several connections between each neuron. The weight characteristic of each arrow regulates how much the activation of one neuron affects the others attached to it. These deep, hidden layers are what deep learning is described as having, and it gets its effectiveness from them. Depending on the nature of the issue and the size of the data set, the number of concealed layers is chosen. Two hidden layers of a deep neural network are depicted in theaccompanying figure. The input layer receives the data.

The data is ingested by each node in the input layer, which then transmits it to the hidden layers. These hidden layers use a linear function to gradually take characteristics from the input layer and transform it. These layers modify the data by adding random parameters, each of which produces a distinct output, and are known as hidden layers since it is unknown what the parameters (weights and biases) in each node are. Thefinal layer, known as the output layer, receives the output produced by the hidden layers and, depending on the objective, either classifies, predicts, or creates samples. Forward propagation is the term for this procedure.

An algorithm, such as gradient descent, assesses mistakes by considering the difference between the original output and the predicted output in a process known as backpropagation. The function's weights and biases are then changed by going backward through the layers in order to correct this inaccuracy. A neural network can reduce error and achieve high accuracy in a given task using both the forward propagation and backpropagation processes. The algorithm improves in accuracy with each repetition. Neural networks come in a variety of forms. CNN-Computer vision and image processing activities are typically handled by CNNs, or convolutional neural networks. CNNs are incredibly effectivein modelling geographical data, whether 2D or 3D video andimages.

RNN-The main use of recurrent neural networks, also knownas RNNs, is the modelling of sequential data, such as text, audio, or any other kind of data that denotes sequence or time.They are frequently employed in natural language processing(NLP) activities.

GANs-Generative adversarial networks, often known as GANs—are frameworks used for unsupervised learning tasks. In essence, this kind of network learns the patterns anddata structure in a way that allows it to produce new examplesthat are similar to those in the original dataset.

Transformer-Transformers is a new class of deep learning model that is primarily used for modelling sequential data tasks, such as those seen in NLP. They are replacing RNNs since this one is significantly more powerful than them.

There are several uses for deep learning in practically every industry, including image identification, finance, and healthcare. Let's discuss a few uses in this area. Medical care: Health care use cases have been ideal for implementing deep learning due to the availability of vast volumes of data and simpler access to accelerated GPUs. Cancer can now be detected from MRI and x-ray images withgreater precision than ever before thanks to image recognitiontechnology. The use of genomes, clinical trial matching, anddrug discovery have also been widely adopted in the healthcare industry. Although automating the field of self- driving automobiles isrisky, it has recently begun to get closer to reality. Deep learning-based models are able to recognise everything from a stop sign to a pedestrian crossingthe street.

II. RELATED SYSTEM

A Comprehensive Unsupervised Framework for Chronic Kidney Disease Prediction

Authors: Linta Antony; Sami Azam; Eva Ignatious; Ryana Quadir; Abhijith Reddy

Beeravolu;Mirjam Jonkman; FrisoDeBoer.
Year: 2021
Objective:
The aim of this project is an intelligent system to classify a patient into classes of 'CKD' or 'Non-CKD' can help the doctors to deal with multiple patients and provide diagnosis faster.
Methodology:
Human kidneys that are damaged and unable to filter the blood and get rid of metabolic waste as they should are said to have chronic kidney disease (CKD). CKD typically takes a sizable length of time to develop gradually. Kidney disease, including CKD, has been found to impact more than 800 million individuals worldwide. Two sets of samples, obtained at least 90 days apart, are necessary to diagnose CKD. You can use values from the past. Creatinine levels, sex, race, and age all affect the estimated glomerular filtration rate (eGFR). Over time, CKD might worsen, and both kidneys may completely stop working. It is critical that medical professionals identify CKD and its accompanying disorders as early as possible.

1. **Computer-Aided Diagnosis of Chronic Kidney Disease in Developing Countries: A Comparative Analysis of Machine Learning Techniques**

Authors: Alvaro Sobrinho; Andressa C.M.Da S.Quciroz;
Leandro Dias Da Silva; Evandro De Barros Costa; MariaEliete Pinheiro; Angelo Perkusich.
Year: 2020
Objective:
The aim of this project is to analyses the usage of machine learning techniques to assist in the early diagnosis of CKD indeveloping countries.
Methodology:
Permanent kidney damage is a hallmark of chronic kidney disease (CKD), a global public health issue. The glomerular filtration rate (GFR), which measures the kidney to determine its function status with reference to the glomerulus, or the blood-filtering unit of the nephron, is a widely used CKD screening test. The costs associated with using software to aid in CKD diagnoses must be as minimal as feasible in the context of developing nations, especially in remote and difficult-to-reach areas. The cost of usage and the effectiveness of the classifiers are both impacted by the quantity of CKD variables utilised during CKD risk classifications. Depending on how many attributes are taken into account during the classification, the machine learning approaches offer varying degrees of accuracy for the CKD diagnosis.

2. **Performance Analysis of Machine Learning Classifierfor Predicting Chronic Kidney Disease**

Authors: Rahul Gupta; Nidhi Koli; Niharika Mahor.
Year: 2020
Objective:
The aim of this project is to predict kidney disease by using some of the selected machine learning algorithms and featureselection methods.
Methodology:
Worldwide, chronic kidney disease (CKD) is a serious health issue that has a significant negative impact on health outcomes, especially in low- and middle-income nations where millions of people routinely perish from a lack of adequate care. Any chronic disease has different stages, and the fatality depends on the stage it reached before being treated. The prevalence of diabetes patients, hypertension, heart disease, mellitus, and a family history of renal failure are all high-risk factors for CKD. Undiagnosed and untreated CKD can result in hypertension and, in severe cases, renal failure if it is not addressed. An industry-standard dataset for chronic kidney disease was obtained for this

article from the UCI machine repository. If detected early and treated appropriately, CKD can help patients in a variety of ways.

3. Features Importance to Improve Interpretability of Chronic Kidney Disease Early Diagnosis

Authors: Pedro A. Moreno-Sanchez

Year: 2020

Objective:

The aim of this project is to enhancing the early diagnosis quality of CKD patients through developing an automated and accurate classifier model based on data pre-processing and feature selection techniques.

Methodology :

The incidence, prevalence, and high financial burden of chronic kidney disease (CKD) on health systems make it a global public health issue. The great majority of CKD patients die of premature causes because their quality of life is significantly impacted by a progressive loss of renal function. Early on, CKD usually shows no symptoms, but later on, symptoms including leg edoema, acute exhaustion and generalised weakness, shortness of breath, loss of appetite, or confusion may surface. The primary goal of treating CKD is to slow the course of kidney impairment, usually by addressing the underlying causes. Delays in diagnosis and treatment frequently result in further kidney damage and health issues, making hemodialyses or even kidney transplantations the only treatments that can keep the patient alive.

4. Assessment Of "Breath Print" in Patients with Chronic Kidney Disease During Dialysis by Non-Invasive Breath Screening of Exhaled Volatile Compounds Using an Electronic Nose

Authors: Omar Zaim; Tarik Saidi; Nezha El Bari; Benachir Bouchikhi

Year: 2019

Objective:

The aim of this project is to investigate exhaled breath of chronic kidney disease (CKD) patients during Haemodialysis (HD).

Methodology:

Due to the increasing decrease in renal function, patients with CKD are at risk for a wide range of consequences, including hypertension, diabetes, and mortality. CKD has recently received a lot of attention and has grown to be a significant public health issue. There are various biomarkers in the breath that can be used as non-invasive diagnostic tools and reflect health status. This paper has shown the potential of an electronic nose device to monitor CKD patients' breath VOCs while they are receiving HD therapy. A definite difference between the breath samples of healthy people, CKD patients before HD, and CKD patients after HD was visible in the box plot depiction. During the four hours of HD, the PCA approach enabled the differentiation between one volunteer patient with CKD's breath samples.

5. Cellular-Level Structure Imaging with Micro-optical Coherence Tomography (μOCT) for Kidney Disease Diagnosis

Authors: Chi Hu; Xiaojun Yu; Qianshan Ding; Zeming Fan; Zhaohui Yuan; Juan Wu; Linba Liu.

Year: 2019

Objective:

The aim of this project is to assessment the feasibility of μOCT for CKD diagnosis by measuring the number of glomeruli within a volume of kidney tissue, which could also be utilized as a parameter for evaluating the severity of CKD.

Methodology:

One of the biggest hazards to global public health is chronic kidney disease (CKD), which can lead to catastrophic conditions like heart disease, renal failure, or even premature death. Although general internists are typically able to manage CKD, this type of treatment is only effective until noticeable symptoms manifest, which can take a very long time. Additionally, it has been claimed that glomeruli can be used to classify CKD according to the phases of disease severity for early therapy. However, the diagnosis is challenging due to the lack of a reliable way to identify the cellular-level microstructures for disease severity characterization. As a result, the treatments may be delayed, and the ideal therapy window may be lost.

6. Support Vector Machine with Purified K-Means Clusters for Chronic Kidney Disease Detection Authors: Utomo Pujianto; Nur A'yuni Ramadhani; Aji Prasetya Wibawa.

Year: 2018

Objective:

The aim of this project is to that the K-Means algorithm and Support Vector Machine algorithm is used to process chronickidney disease detection.

Methodology:

A kidney condition known as chronic renal disease is characterised by a progressive loss of kidney function overseveral years. Up until the kidney loses 25% of its function, this illness is noticeable. In order to give pertinent and appropriate treatment that is in line with the diagnosis of chronic renal disease, a correct and acceptable diagnosticapproach is required. The diagnosing process can be carriedout easily with the help of modern technology. By using datamining techniques like clustering and classification, the diagnosis can be made. This article aims to investigate theapplication of the support vector machine method and the K-Means algorithm as clustering and classification algorithms,respectively. Data on the pure cluster are determined usingthe clustering procedure.

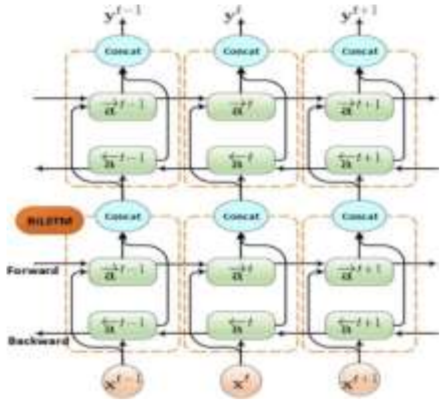
III. PROPOSED SYSTEM

On the Internet of Medical Things (IoMT) platform, a deep convolutional neural network has been proposed for the early detection, segmentation, and diagnosis of chronic renal failure. A Deep Convolutional Neural Network (DCNN) approach has been proposed for the early detection, segmentation, and diagnosis of chronic renal disease, and it isemployed in this study to predict lab test timing series data of CKD. After capturing a raw image for the proposed DCNN system, the noise must be minimised because it can be a significant segmentation issue. Noise is reduced using the wavelet-based pretreatment approach. The renal region is segmented in the designated RPN picture, and additional processing features of characteristics that have been chosen to suggest a problem in the kidney are extracted.

A.BiLSTM:

These are an improvement over LSTMs. Each training sequence is presented both forward and backward in bidirectional LSTMs in order to differentiate recurrent neuralnetworks. The same output layer is connected to both sequences. Bidirectional LSTMs have full knowledge of every point in a particular sequence, as well as everything thatcame before and after to it The human brain employs its senses to gather data from words, sounds, or entire phrases that may not make sense at first but may do so in a later context. Conventional recurrent neural networks can only retrieve information from the prior context. Contrarily, with bidirectional LSTMs, data is processed in both directions within two hidden layers and then pushed towards a single output layer to retrieve information. This facilitates bidirectional LSTM access to long-range context.

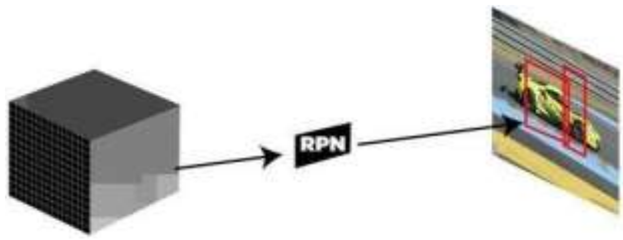
Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, No. 3, May : 2023



BiLSTM

B. Region Proposal Network:

This region proposal network takes convolution feature map that is generated by the backbone layer as input and outputs the anchors generated by sliding window convolution applied on the input feature map.



C. Grey Level Co-occurrence Matrix:

Kidney illness texture analysis for parametric variations using the Grey Level Co-occurrence Matrix (GLCM) Three Pyoderma variants—Boil, Carbuncle, and Impetigo Contagiosa—were used in the studies using GLCM. From the photos used in the experiment, the GLCM parameters energy, correlation, contrast, and homogeneity were retrieved for each colour component. The coarseness, linear dependency, textural uniformity, and pixel distribution of the texture are each represented by contrast, correlation, energy, and homogeneity. The GLCM parameters' histograms' analysis revealed that the aforementioned textural aspects are disease- dependent. By using a suitable deep learning algorithm, the method can be employed for the accurate identification of CKD illnesses.

D. Convolutional Neural Network (CNN):

To examine visual scenes, deep learning techniques like CNNs are used. A fully linked layer that produces the desired output and one or more hidden layers that extract the properties from movies or images are its distinguishing features. In contrast, the image on the computer is a 3D array (width, height, and depth) of numbers with a range of 0 to 255. It is just colour pixels; if there is only one channel, the image is in grayscale, black, and white. Additionally, if photos are RGB, the channels are three colours. Due to its precise outputs, CNN Deep Network has demonstrated remarkable performance in numerous image processing competitions. The convolutional layer, the activating function, the pooling layer, and the fully connected layer are the fundamental parts of a basic convolutional neural network.

Layer of Convolution: Several filters can be used to extract various features once a filter (known as a kernel) in the convolutional layer determines whether there are any patterns in the input images (original image). The filter is small enough to be able to scan the entire image and use the proper mathematics to extract the features between the filter and the pixels. erarchical structure with several

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, No. 3, May : 2023

layers is CNN.
The filter settings are reset during the periodic training phase, and after the network has trained for a certain number of epochs (epochs mean all training samples have been entered concurrently), these filters begin searching for various properties in the image. Using the initial hidden layers, straightforward and obvious features are recovered, such as edges in different directions. As we delve further into the network's hidden tiers, the intricacy of the attributes that mustbe identified and extracted increases.

Pooling layer :

The pooling is done to cut down on the size of the activation maps. Although it's not necessary, doing this keeps you from being in an uncomfortable scenario. As big arrays are scaled down, clustering's basic concept is straightforward.

Fully-connected Layer :

The input layer's range can be between 0 and 1. In the convolution layer, where the neurons are used for image processing to detect edges, curves, etc., each neuron is considered a filter, with the filter being produced for the data network depth. Each of the convolution layer's filters will have unique visual characteristics, including vertical and horizontal edges, colours, textures, and densities. The feature extractor array for the entire image is increased by each neuron. Additionally, the amount of input and parameters are compressed, and overfitting is decreased by sandwiching the pooling layer between subsequent convolutional layers. In other words, the pooling layer's primary job when the input is an image is to resize and compress the image.

IV. METHODOLOGY

CKD Screening Dashboard :

The online mobile-friendly tool asks a series of disease attributes.Based on the user's responses, the tool then provides information about interpreting test results as well as recommended actions and resources

Dataset Preparation and exploration:

The first step of a data science task is to obtain, gather, and measure the necessary and targeted data from available internal or external data sources, and then compiled into an established system.
It perform intense exploratory analysis using the dataprep.edamodule

Data Pre-processing:

Data preprocessing is a data mining technique that transformsraw data into an understandable format. This process has four main stages – data cleaning, data integration, data transformation, and data reduction.Data cleaning will filter, detect, and handle dirty data to ensure quality data and quality analysis results. In this case, there may be noises of impossible and extreme values and outliers, and missing values. The errors may include inconsistent data and redundant attributes and data.As the first step, null values within the dataset will beidentified, and appropriately replaced if possible.

Feature Selection:

Recursive Feature Elimination (RFE) removes features recursively, building a model based on other features. It applies greedy search to find the most efficient subset of features.

Feature Extraction:

Choosing those features which are somehow correlated todepression positive (correlation > 0.1)
Correlation heatmap is used to list all the correlationcoefficients in order to identify multicollinearity

BilSTM Classification Model:

In this module the proposed model based on Bi Long Short- Term Memory (LSTM) with 14 hidden units (neurons) to predict CKD and Stages of disease.

CKD Test Data:

Taking a symptom test to check the presence of CKD andstages of CKD.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, No. 3, May : 2023

Take inputs from user and give him the result andrecommendation

CD Prediction Module:

The test data will be passed to the BiLSTM model classifier topredict its target class label of disease prognosis.

Test Result:

Predicting the CKD condition and giving instructions with respect to the predict value.

Patient or Doctor:

Registration: The Registration module is an integrated CKD Patiet management system, which captures complete andrelevant CKD information. It is used to create new users, whocan login to the webUI.

Login: This module deals with the security matters, user logons and authentications.

Take Symptom test to predict the type of CKD.

Admin

The person who maintains all these functions in between actors and will take care of overall system.

Proper authorization will be done to take care of who is accessing the database – Administrator, Patient, Doctor or Guardian.

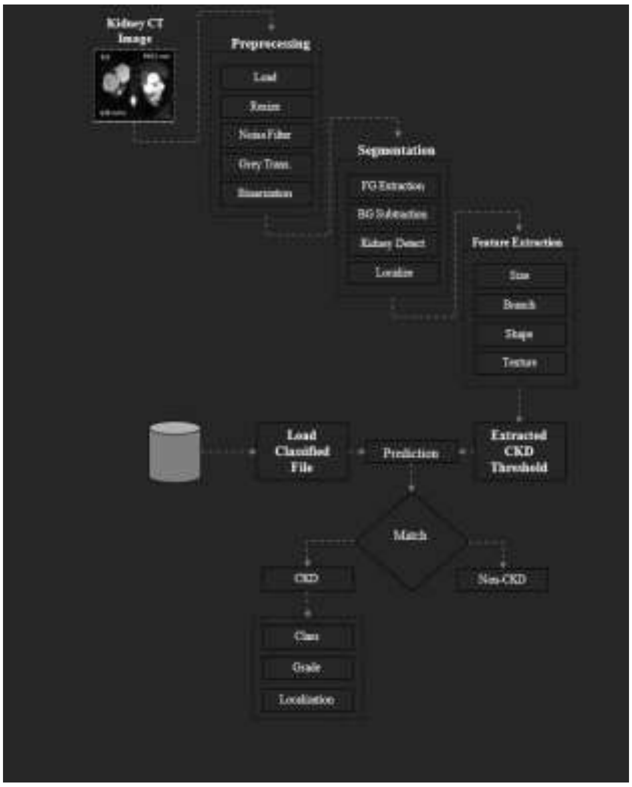
Performance Metric:

The confusion matrix is then used to determine theperformance metrics of accuracy, precision, recall, and F1- score, based on those classifications.

The confusion matrix tabulates the predicted class vertically and the actual class horizontally.

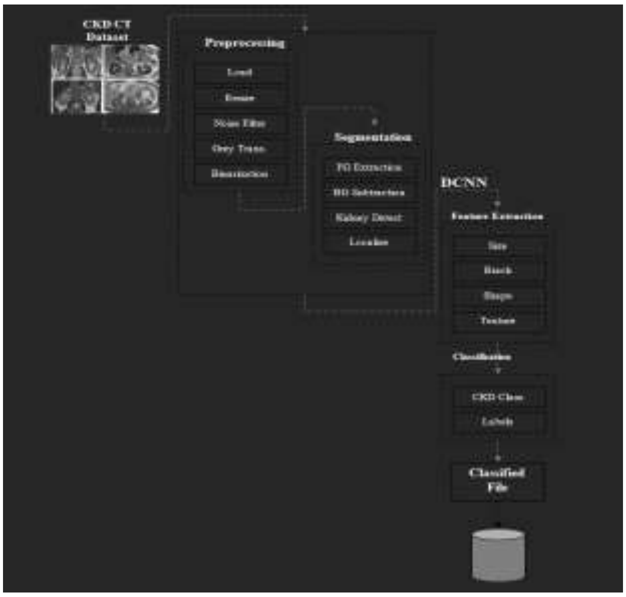
I. SYSTEM ARCHITECTURE

II. Lab Test

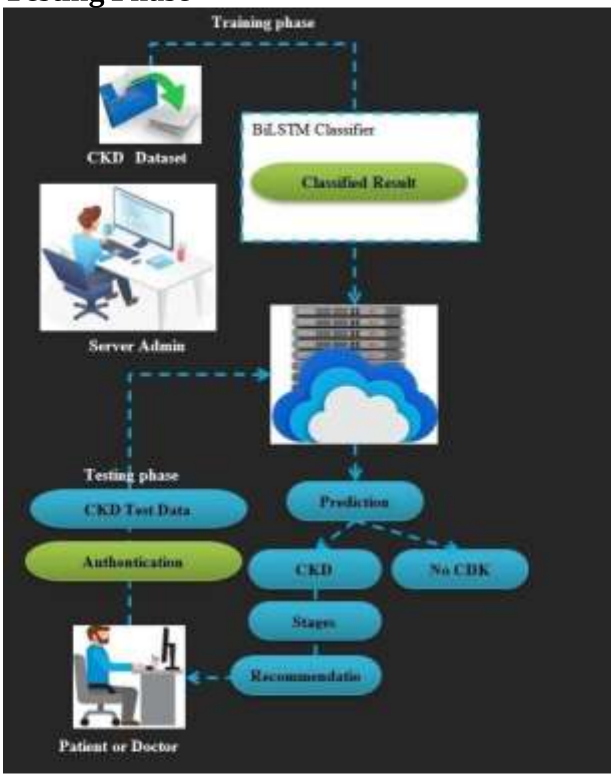


Industrial Engineering Journal
ISSN: 0970-2555
Volume : 52, Issue 5, No. 3, May : 2023

System Architecture–CT Kidney Image TrainingPhase



Testing Phase



IV. CONCLUSION

The newest field of study is automated disease diagnosis using deep learning and medical imagery. In general, kidney radiology imaging applications of deep learning are still in their infancy. On the other hand, deep learning will advance since it has a number of advantages over other imaging techniques, and efforts are being made to overcome the present difficulties. The directions for the proposed system centre on using more images from earlier studies and diagnosing all aspects of kidney disease in one process by utilising deep learning algorithms to create multi-models that perform detection, classification, segmentation, and other tasks; this aids the medical staff in accurately diagnosing the patient's condition from all angles and ensures that there is never a lack of diagnostic information, which results in the se Additionally, in the future, radiology practises may combine advanced data analytics-based AI tools (such as machine and deep learning techniques).

V. FUTURE SCOPE:

To maximise the value of the huge and dispersed data sets available today, integration of the kidney CT image data sources is becoming just as important as data mining. KCT Distributed processing architectures like grids and peer-to-peer networks can be used to integrate data across geographically separated sites. A special decentralised service- based big data design for grid databases is needed to integrate various data models on database systems and combine data from many sources to obtain the necessary information. Future research should be a priority in a new service-based design for system integration on grids.

VI. REFERENCE

1. Klepaczko, A.; Majos, M.; Stefa ´ nczyk, L.; Ejkefjord, E.; Lundervold, A. Whole kidney and renal cortex segmentation in contrast enhanced MRI using a joint classification and segmentation convolutional neural network. Biocybern. Biomed. Eng. **2022**, 42, 295–311.
2. Fuat, T.; Murat, L.; BARI¸SÇI, N. Machine Learning of Kidney Tumors and Diagnosis and Classification by Deep Learning Methods. Uluslararası Mühendislik Ara¸stırma Geli¸stirme Derg. **2019**, 11, 802–812.
3. Myronenko, A.; Hatamizadeh, A. 3d kidneys and kidney tumour semantic segmentation using boundary-aware networks. arXiv **2019**,
arXiv:1909.06684.
4. Alelign, T.; Petros, B. Kidney stone disease: An update on current concepts. Adv. Urol. 2018, 2018, 3068365.
5. Bai, W.; Fadil, Y.; Chadli, A.; Dakir, M.; Debbagh, A.; Aboutaeib, R. Correlation between CT and anatomopathological staging of kidney cancer. Int. J. Surg. Case Rep. 2021, 80, 105687.
6. van Oostenbrugge, T.J.; Fütterer, J.J.; Mulders,
P.F. Diagnostic imaging for solid renal tumours: A pictorial review. Kidney Cancer 2018, 2, 79–93.
7. Kang, L.; Zhou, Z.; Huang, J.; Han, W.;
Member, I. Renal tumors segmentation in abdomen CT Images using 3D-CNN and ConvLSTM. Biomed. Signal Process. Control 2022, 72, 103334.
8. George, M.; Anita, H. Analysis of Kidney Ultrasound Images Using Deep Learning and Machine Learning Techniques: A Review. In Pervasive Computing and Social Networking; Springer: Berlin/Heidelberg, Germany, 2022;pp. 183–199.
9. Yang, E.; Kim, C.K.; Guan, Y.; Koo, B.B.; Kim,
J.H. 3D Multi-Scale Residual Fully Convolutional Neural Network for Segmentation of Extremely Large-Sized Kidney Tumor. Comput. Methods Programs Biomed. 2022, 72, 106616.
10. Muhamed Ali, A.; Zhuang, H.; Ibrahim, A.; Rehman, O.; Huang, M.; Wu, A. A machine learning approach for the classification of kidney cancer subtypes using miRNA genome data. Appl. Sci. 2018, 8, 2422.