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TRANSFER LEARNING BASED DL MODEL OF A CROSS-RESIDUAL NETWORK

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ABSTRACT:

The kidneys play a crucial role in human health by filtering the blood. Maintaining normal amounts of sodium, potassium, and blood pH depends on the kidneys functioning normally. Humans are increasingly susceptible to renal failure as a result of modern living, diet, and illnesses like diabetes. Timely therapy of renal stones requires accurate early prognosis. The success rate of image processing-based diagnostic methods is higher than that of other methods of identification. A DL model of a cross-residual network (XResNet-50) was presented for renal stone categorization by Yildirim et al.2021. For precise diagnostics, the suggested XResNet-50 uses four layers of computing. ResNet layers at every step of the process boost the model's ability to identify features. According to the experiments, the suggested cross-layered model has a better precision (96.23%) than the other proposed models.

1. INTRODUCTION

Individuals with chronic kidney disease (CKD) experience progressive loss of renal capability north of a while to years. [2][5] At first, patients might encounter no signs;however, they may develop limb edema, fatigue, sickness, lack of hunger, and disorientation later on. The endocrine dysfunction of the kidneys can lead to bone disease, anemia, and high blood pressure, all of which are often caused by stimulation of the renin-angiotensin system [2]. [3][4][10] Increased mortality and hospitalisation rates are associated with the circulatory problems that CKD patients face. [11]Diabetes, hypertension, glomerulonephritis, and polycystic kidney infection are potential main drivers of ongoing kidney disappointment. [5]A history of severe renal illness in the family is one risk factor [6]. For diagnosis, albumin tests and the blood's estimated glomerular filtration rate (eGFR) are used.An ultrasound or renal sample [7] can help find the root of the problem. There are multiple severity-based queuing methods in use today, [5]. [12]People who are at risk should be screened [13]. Medication to reduce blood pressure, blood sugar, and lipids may be used as an initial therapy [7]. Angiotensin converting enzyme inhibitors (ACEIs) or angiotensin II receptor blockers (ARBs) are normally utilized as the first-line treatment for hypertension [9] in light of their capacity to forestall renal illness and lower the gamble of cardiovascular sickness. Circle diuretics can be utilized to lessen liquid maintenance and

hypertension [14]. [15][9]You ought to avoid NSAIDs [16]. [9] In addition to these medications, doctors advise their patients to lead busy lives and make adjustments to their diets, such as eating less sodium and more protein. Therapies for iron deficiency and bone disease may likewise be required. [18][19] Patients with end-stage renal disappointment might require either hemodialysis or peritoneal dialysis or a kidney relocate. [8]In 2016, 753 million individuals worldwide were afflicted with chronic renal disease; 417 million women and 336 million men. [1][20] The number of fatalities it caused in 2015 was 1.2

million, up from 409,000 in 1990. [6][21] Hypertension represents 550,000 fatalities yearly, followed by diabetes at 418,000 and glomerulonephritis at 238,000. [6]

II.LITERATURE SURVEY

In the last decade, chronic renal disease has been responsible for roughly 58 million fatalities around the globe, according to the globe Health Organization [1]. Moreover, more than two million people around the globe require dialysis or a kidney donation to stay alive due to renal failure. However, this figure may only reflect 10% of those who truly require therapy in order to live [2]. Data mining provides a forecast tool to derive usable knowledge and aid partners like health-related organisations by sifting through large amounts of data in search of patterns and

insights. Images, texts, sequences, websites, networks, and graphs or even physical spaces can all be mined using data mining [3].

The banking organization, for example, has used it widely for fraud prediction and credit rating, marketing, quality control, and repair plans up-selling and cross-selling [4]. The discovery of oil spills is just one of many potential uses [5]. Other applications include medical diagnostics, abnormality detection, flaw diagnosis, and e-mail screening. Stakeholders can use data mining's classification, clustering, association rule mining, regression analysis, and anomaly detection tools to examine the data from a variety of perspectives in light of the numerous issues they have raised. In particular, classification is a data mining method that is employed to aid in the analysis of data and the prediction of possible outcomes [6, 7] by teaching a set of characteristics for the purpose of evaluating a set of attributes with which the practitioner is unfamiliar.

Chronic Kidney Disease (CKD) is being diagnosed with more and more people, but there is currently no widely recognised prognostic model for CKD, as reported in [8]. Prediction of CKD is the primary focus of this study. Patients' renal diseases are categorised using a supervised categorization method, such as a Two-Class Neural Network or a Two-Class Decision Forest. For the purpose of creating categorization models for distinguishing between people with chronic kidney disease (CKD) and those with non-chronic kidney disease (NCKD), Microsoft Azure Machine Learning Studio [9] and the Two-Class Decision Forest and Two-Class Neural Network methods were utilized. Other algorithms that have been discussed in a survey by [10] include linear discriminant, decision trees, linear support vector machines, quadratic support vector machines, k-nearest neighbors, weighted k. In 2016, four chronic kidney diseases were predicted, including Nephritic Syndrome, Chronic Glomerulonephritis, and Acute Renal Failure. SVM and ANN, both guided algorithms, were used to make the renal illness prediction. When compared to SVM [11], the findings demonstrated that ANN was the superior predictor due to its higher precision and shorter processing time.

Patients with renal illness have been classified as either chronic or non-chronic using Naive Bayes and KNN algorithms in recent research. Best First Search and the Wrapper approach in WEKA [12] were used to narrow down candidate features for inclusion in the final model (BFS). The findings demonstrated that the algorithms' efficiency improved with fewer characteristics. On a smaller sample consisting of hand-picked characteristics, WEKA's KNN classifier implementation, the IBK classifier, outperformed the competition [13]. The forecast method has also advanced the use of data pre-processing and data mining methods to determine whether

or not there is a connection between the observed factors or parameters and the outcome of the patients [5]. Two dynamic calculations were utilized to reenact the choice rules to estimate the death rate in view of explicit elements that were made sense of by clinical staff at four dialysis offices.

On renal dialysis information, we analyzed the exhibition of three particular characterization calculations — ANN, DT, and Coherent Relapse (LR) — in [14]. Compared to the DT and LR algorithms, the experimental findings demonstrated that ANN achieved the greatest precision. [15] suggested a different renal failure prediction model using Apriori and k-means algorithms on a total of 42 characteristics. For the purpose of the analysis, the calibration graphs and the Receiver Operating Characteristic (ROC) curve were utilized.

Back Propagation Algorithm (BPA), Support Vector Machine (SVM), and Radial Basis Function (RBF) were some of the additional algorithms for renal stone diagnosis that were taught and evaluated in [16]. The primary objective of this study was to improve doctor productivity and speed up the diagnostic process. The trial findings showed that BPA greatly enhanced the categorization technique for medicinal applications.

Finally, [17] utilised Support Vector Machines (SVM) and Random Forest (RF) with varying kernel values to categorise additional illnesses like malignancy, liver disease, and heart disease. It was determined that different kernel functions yielded various outcomes, and that these differences could be optimised for with careful parameter selection.

III. PROBLEM STATEMENT

In most cases, medical imaging techniques provide an accurate diagnosis of a variety of illnesses. Many machine learning techniques and deep learning techniques are used to develop kidney stone detection using CNN, which reduces the doctor's mental fatigue. A convolutional brain organization (CNN) is a sort of brain network that orders highlights separated from an info picture by using another brain organization. The brain network performs arrangement in view of the recovered component signals. Consequences be damned performed well in both the preparation and test sets for 2D location. The principal trouble in adjusting Just go for it to 3D clinical pictures is that it requires 2D photographs as info. The model has difficulty detecting the kidney's extremities, either because of its reduced size or the attenuation of distinctive characteristics. These are

more prone to go undetected, as was the case with the kidneys' bottom thirds.

IV.ARCHITECTURE AND METHODOLGY

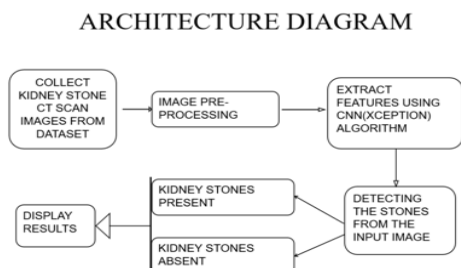
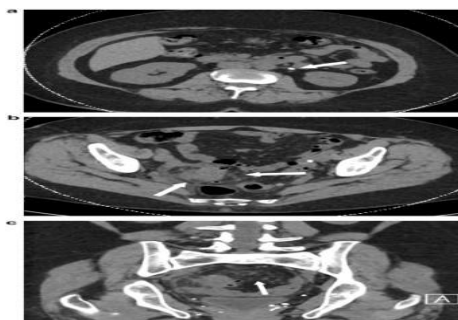


Fig 6 BLOCK DIAGRAM

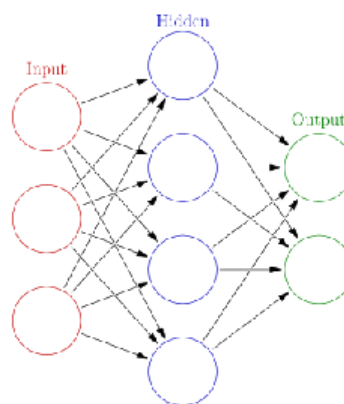
Our study seeks to solve these problems by developing an adaptable, automatically predictive system for kidney stones in real time.Using RESNET50 and CNN, we suggested a technique for extracting meaningful characteristics from photos. Additionally, we will create a scalable system that employs transfer learning to detect kidney stones in real time. We will develop a framework using deep learning that aims to diagnose the kidney stones using images . RESNET50 increases the feature extraction capability enhancing the accuracy and efficiency.



V.IMPLEMENTATION

The process of machine learning begins with the construction of a model, which is then educated using a set of training data, after which it is able to analyse more data and provide predictions. Machine learning systems have made use of, and conducted research on, a wide variety of different models.

Artificial neural networks



An artificial neural network is similar to the vast network of neurons in the brain in that it is made up of connected nodes. Artificial neurons are represented by the spherical nodes in this picture, and connections between them are shown by the arrows.

Biological neural networks form the basis of animal brains, and artificial neural networks (ANNs), also known as connectionist systems, are a kind of computer system that is loosely modelled after these biological neural networks. These kinds of systems "learn" to carry out tasks by thinking about examples, often without being programmed with any rules that are relevant to the jobs themselves.

An ANN is a kind of model that is constructed using a network of interconnected units, or nodes, artificial neurons. These neurons are intended to generally imitate the neurons that are tracked down in a human mind. Each connection, which is analogous to the synapses in a real brain, has the ability to convey information in the form of a "signal" from one artificial neuron to another. When it receives a signal, an artificial neuron has the ability to process it and then pass on the information to other artificial neurons that are linked to it. In the majority of ANN implementations, the message at a linkage among both biological neuron is a true number, and indeed the result from each perceptron is tabulated by some quasi function of the sum of its inputs. To put it another way, the signal at a neuronal linkage is a real number. Edges are a term used to describe the connections that are made between artificial neurons. The weight of an artificial neuron or edge will normally change as learning progresses whether it is an artificial neuron or edge. The intensity of the signal at a connection may be increased or decreased depending on the weight. The signal may only be sent if the overall signal strength is greater than a certain threshold, which may be present in artificial neurons.

Layered organisation is a common method for artificial neurons. The inputs to the various levels may be subjected

to a variety of changes, depending on the layer. Signals stream from the first layer, which is known as the info layer, the whole way to the last layer, which is known as the output layer. This may include travelling through the layers more than once.

The purpose of the ANN technique, the original idea was to try to solve problems in the same way that the human brain would. However, as time passed, the emphasis shifted from biology to completing particular tasks, which resulted in departures from biological norms. There are many applications for artificial neural networks, such as computer vision, voice recognition, machine translation, filtering in social networks, playing board games and videogames, and medical diagnosis.

The use of numerous hidden layers inside an artificial neural network is what constitutes deep learning. This method works by simulating the manner in which the human brain converts light and sound into the senses of vision and hearing. Computer vision and voice recognition are two areas that have seen significant progress because of deep learning. [57]

Decision trees

In decision tree learning, the nodes represent observations, and the branches provide judgements about the goal value of the item based on those observations. (represented in the leaves). It may be used as a kind of predictive modelling in the areas of statistics, data mining, and machine learning. The objective variable in classification trees may take on an infinite number of values. The nodes of such trees reflect individual traits, while the leaves represent class designations. When the dependent variable may take on a continuous range of values (often represented by real numbers), a decision tree style known as a regression tree is utilised. A decision tree is a useful tool for decision analysis because it may graphically and clearly reflect choices and the decision-making process. A decision tree is used to visualise data in the area of data mining, and the resulting classification tree may be utilised as a guiding factor in making choices.

Support vector machines

For the reasons for order and relapse, support vector machines (SVMs), otherwise called help vector organizations, are a bunch of interconnected regulated learning calculations. When given a set of training examples labelled with one of two classes, a support vector machine (SVM) training process will generate a model that can determine which class a new example belongs to. [58] During training, a support vector machine (SVM) is a binary, non-probabilistic, linear classifier, it may be employed in a probabilistic classification situation with the help of techniques like Platt scaling. Support vector

machines (SVMs) are not limited to linear classification; by the use of the kernel method, which translates their inputs implicitly into high-dimensional featurespaces, they are also capable of doing non-linear classification efficiently.

Regression analysis

When it comes to estimating the nature of the connection that exists between the variables that are fed into the model and the characteristics that are connected with those models, regression analysis makes use of a wide range of statistical techniques. Linear regression, in which a mathematical criterion like ordinary least squares is used to fit a straight line to the data, is the most prevalent type of regression analysis. This type of linear regression is the most prevalent. The latter is sometimes supplemented by regularization (mathematics) approaches, such as ridge regression, in an effort to reduce instances of overfitting and bias. Microsoft Excel's trendline fitting feature uses polynomial regression [59], when dealing with quasiproblems, some examples of go-to modeling techniques include logistic regression, which is used for statistical classification, and kernel regression, which reveals non-linearity by mapping input parameters to a higher-dimensional space using the kernel function.

Genetic algorithms

The term "genetic algorithm" refers to both a search algorithm and a heuristic technique. Aevolutionary algorithms (GA) are search algorithms that use pattern recognition methods like mutations and crossovers to produce new genetic traits in the hope of finding effective solutions to a particular issue. This mimics the process of natural selection. Throughout the 1980s and 1990s, genetic algorithms were used in the field of machine learning. [60] [61] On the other hand, methods from machine learning have been applied to genetic and adaptive methods in order to enhance their current effectiveness. [62]

Training models

Machine learning models, in general, call need a substantial amount of input data in order to function well. While training a machine learning model, it is often necessary to gather a sizable and representative subset of the data included in the model's training set. A lot of text, a lot of pictures, or data from individual service users are all examples of data that could be included in the training set. While training a machine learning model, one thing to keep an eye out for is something called overfitting.

Federated learning

Federated learning is a novel approach to decentralizing the training of machine learning algorithms. This removes the need that users provide their data to a centralised server, therefore preserving the users' right to privacy. This also boosts efficiency since it distributes the process of training over many different devices. For instance, Gboard makes use of federated deep learning to train querying forecasting model locally on users' cellular telephones. This eliminates the need for users to submit Google their personal search queries.

VI RESULTS

Splitting Dataset into Train & Validation

```
1 data_gen = ImageDataGenerator(  
2     rescale = 1.0/255,  
3     validation_split=0.20  
4 )  
5  
6 train_data = data_gen.flow_from_directory(  
7     data_directory,  
8     classes=class_names,  
9     target_size=(200,200),  
10    batch_size=32,  
11    seed=100,  
12    subset='training',  
13    class_mode='categorical'  
14 )  
15  
16 validation_data = data_gen.flow_from_directory(  
17     data_directory,  
18     classes=class_names,  
19     target_size=(200,200),  
20     seed=100,  
21     batch_size=32,  
22     subset='validation',  
23     class_mode='categorical'  
24 )  
  
Found 9959 images belonging to 4 classes.  
Found 2487 images belonging to 4 classes.
```

Created Model and displaying Model summary:

Model: "sequential"

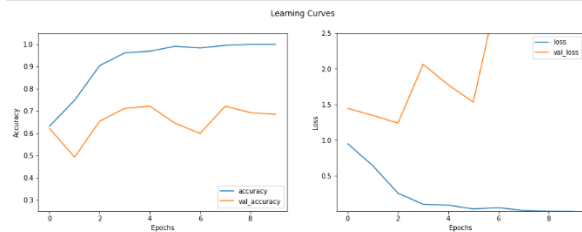
Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 198, 198, 32)	896
max_pooling2d (MaxPooling2D)	(None, 99, 99, 32)	0
conv2d_1 (Conv2D)	(None, 97, 97, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 48, 48, 32)	0
conv2d_2 (Conv2D)	(None, 46, 46, 64)	18496
max_pooling2d_2 (MaxPooling2D)	(None, 23, 23, 64)	0
conv2d_3 (Conv2D)	(None, 21, 21, 64)	36928
max_pooling2d_3 (MaxPooling2D)	(None, 10, 10, 64)	0
conv2d_4 (Conv2D)	(None, 8, 8, 128)	73856
max_pooling2d_4 (MaxPooling2D)	(None, 4, 4, 128)	0
conv2d_5 (Conv2D)	(None, 2, 2, 128)	147584
max_pooling2d_5 (MaxPooling2D)	(None, 1, 1, 128)	0
flatten (Flatten)	(None, 128)	0
dense (Dense)	(None, 512)	66048
dense_1 (Dense)	(None, 4)	2052

```
=====
Total params: 355,108
Trainable params: 355,108
Non-trainable params: 0
=====
```

Fitting the Model and Training the model:

```
1 hist=model.fit(train_data,  
2     batch_size = 32,  
3     steps_per_epoch=100,  
4     epochs=10,  
5     validation_data=validation_data,  
6 )  
  
Epoch 1/10  
100/100 [=====] - 177s 2s/step - loss: 0.9487 - accuracy: 0.6313 - val_loss: 1.4445 - val_accuracy: 0.6216  
Epoch 2/10  
100/100 [=====] - 157s 2s/step - loss: 0.6402 - accuracy: 0.7478 - val_loss: 1.3454 - val_accuracy: 0.4922  
Epoch 3/10  
100/100 [=====] - 147s 1s/step - loss: 0.2553 - accuracy: 0.9041 - val_loss: 1.2380 - val_accuracy: 0.6542  
Epoch 4/10  
100/100 [=====] - 178s 2s/step - loss: 0.1000 - accuracy: 0.9613 - val_loss: 2.0627 - val_accuracy: 0.7117  
Epoch 5/10  
100/100 [=====] - 163s 2s/step - loss: 0.0873 - accuracy: 0.9680 - val_loss: 1.7754 - val_accuracy: 0.7218  
Epoch 6/10  
100/100 [=====] - 161s 2s/step - loss: 0.0342 - accuracy: 0.9909 - val_loss: 1.5329 - val_accuracy: 0.6450  
Epoch 7/10  
100/100 [=====] - 154s 2s/step - loss: 0.0516 - accuracy: 0.9833 - val_loss: 3.1212 - val_accuracy: 0.5991  
Epoch 8/10  
100/100 [=====] - 155s 2s/step - loss: 0.0128 - accuracy: 0.9950 - val_loss: 3.2750 - val_accuracy: 0.7214  
Epoch 9/10  
100/100 [=====] - 149s 1s/step - loss: 0.0019 - accuracy: 0.9997 - val_loss: 3.1217 - val_accuracy: 0.6028  
Epoch 10/10  
100/100 [=====] - 149s 1s/step - loss: 2.3149e-04 - accuracy: 1.0000 - val_loss: 3.1795 - val_accuracy: 0.6040
```

```
1 # Evaluate the model
2
3 plt.figure(figsize=(15,5))
4 plt.subplot(1,2,1)
5 plt.plot(hist.history['accuracy'],label='accuracy')
6 plt.plot(hist.history['val_accuracy'],label='val_accuracy')
7 plt.xlabel('Epochs')
8 plt.ylabel('Accuracy')
9 plt.ylim([0.25,1.05])
10 plt.legend(loc='lower right')
11
12 plt.subplot(1,2,2)
13 plt.plot(hist.history['loss'],label='loss')
14 plt.plot(hist.history['val_loss'],label='val_loss')
15 plt.xlabel('Epochs')
16 plt.ylabel('loss')
17 plt.ylim([0.005,2.5])
18 plt.legend(loc='upper right')
19 plt.suptitle('Learning Curves')
20 plt.show()
```

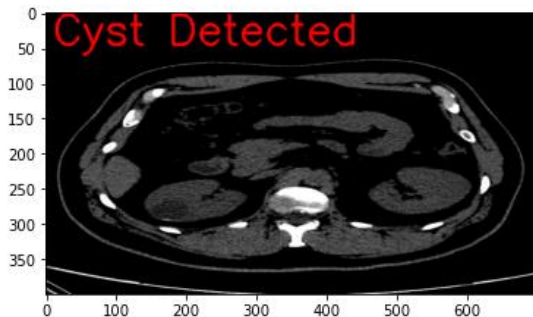


Creating Function for the deployment of model:

```
1 import cv2
2
3 def Prediction(file_path):
4     img = image.load_img(file_path)
5     img_array = image.img_to_array(img)
6     resized_array=tf.image.resize(img_array, [200, 200])
7     x = resized_array/255.0
8     x = (np.expand_dims(x,0))
9     y = model.predict(x)
10    predict = np.argmax(y)
11    img = cv2.imread(file_path)
12    img = cv2.resize(img, (700,400))
13
14    if predict == 0 :
15        cv2.putText(img, 'Cyst Detected', (10, 45), cv2.FONT_HERSHEY_SIMPLEX,2.0, (255, 0, 0), 4)
16    elif predict == 1:
17        cv2.putText(img, 'Normal Detected', (10, 45), cv2.FONT_HERSHEY_SIMPLEX,2.0, (255, 0, 0), 4)
18    elif predict == 2:
19        cv2.putText(img, 'Stone Detected', (10, 45), cv2.FONT_HERSHEY_SIMPLEX,2.0, (255, 0, 0), 4)
20    else:
21        cv2.putText(img, 'Tumor Detected', (10, 45), cv2.FONT_HERSHEY_SIMPLEX,2.0, (255, 0, 0), 4)
22    plt.imshow(img)
```

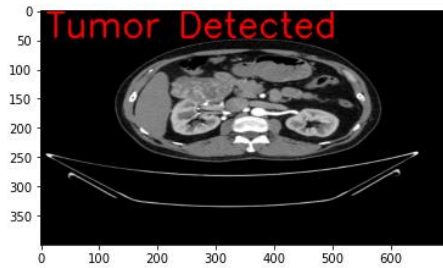
Predicted: Cyst detected

1/1 [=====] - 0s 169ms/step



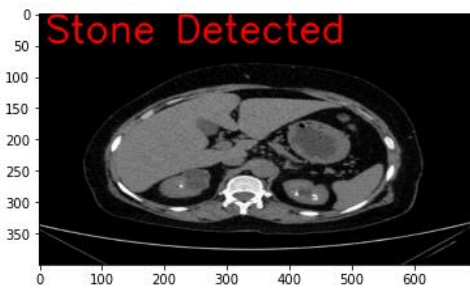
Predicted: Tumor detected

1/1 [=====] - 0s 26ms/step



Predicted: Stone detected

1/1 [=====] - 0s 50ms/step



Predicted: Normal detected

1/1 [=====] - 0s 51ms/step



VII CONCLUSIONS AND SCOPE

The proposed research shed light on how CKD patients are diagnosed so that they can address their condition and receive treatment early on. A total of 400 cases were analyzed, and 24 features were discovered. The dataset was split in half, with one quarter utilised for testing and validation and the other half for training. Mean and mode statistical measures were used to replace missing nominal and numerical values and eliminate outliers from the

dataset, respectively. The most strongly representative CKD characteristics were chosen using the VGG Hybrid Model indicating the positive cases. The scope of the work is to improvise a solution with loss estimation and its improved accuracy for all different dataset chosen in real time.

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