CLASSIFYING KIDNEY DISEASE USING DEEP LEARNING ALGORITHMS

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Masters of Science in Computer Science and Engineering

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APPROVAL

This Thesis titled **"Classifying Kidney Disease Using Deep Learning Algorithms"**, submitted by Amina Akter, ID No: 221-25-086 to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 17-01-2023.

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I hereby declare that, this project has been done by me under the supervision of **Dr. Md Zahid Hasan, Associate professor, Department of CSE,** Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Deep learning algorithms in clinical imaging for the kidney in stomach computed tomography (CT) images have been constrained. Due to this, our main goal is to apply deep learning models along with a suggested training scheme to achieve precise and actual results of the division. Additionally, this group hopes to provide the community with an open-source, unedited dataset of stomach CT images for use in developing and testing deep-learning classification organizations that can segment kidneys and identify kidney disease. The proposed methodology is to detect and classify kidney disease by implementing a TensorFlow library from the computed tomography images of the human kidney using Convolutional Neural Network (CNN) architecture deep learning. In the proposed methodology after using the TensorFlow framework with VGG16 architecture, we achieved 99.13% accuracy in the case of training and 99.63% in validation respectively. Besides, we additionally looked at our model without TensorFlow VGG16, the exactness of preparing and approval precision are 99% and 99% seperately. The TensorFlow model beat the keras model with additional productive and precise outcomes.

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CHAPTER 1
Introduction

1.1 Introduction

The kidneys are a pair of small, hand-sized organs that are located at the base of the rib cage. On either side of the spine, there is a kidney. A healthy body depends on having functioning kidneys. They are primarily responsible for removing side effects, excess water, and other debasements from the blood. These poisons are stored in the bladder and then expelled during urination. The pH, salt, and potassium levels in the body are also controlled by the kidneys. They generate substances that regulate the production of red platelets and direct the circulatory strain. Even a kind of vitamin D that helps the body retain calcium is produced by the kidneys. About 58% adult Bangladeshi are affected by kidney disease. It occurs when your kidneys suffer damage and are unable to perform their function. Diabetes, hypertension, and various other long-term (chronic) illnesses may cause harm. Kidney disease can result in various illnesses such as weak bones, nerve damage, and poor health. If the condition worsens over time, your kidneys could eventually stop functioning altogether. This suggests that renal function will likely be replaced by dialysis. Dialysis is a medical procedure that uses a machine to filter and route the blood. Although it can prolong your life, it cannot treat kidney disease [1]. Persistent kidney disease is the most well-known kind of kidney infection. Chronic kidney disease is a protracted ailment that eventually fails. Hypertension frequently contributes to it. Because it can squeeze the glomeruli, hypertension is dangerous for the kidneys. The tiny kidney veins known as glomeruli are where blood is cleansed. After some time, the damaged arteries caused by the increased strain lead to a reduction in kidney function. Eventually, kidney function will deteriorate to the point that the kidneys are no longer able to perform their role as intended. An individual would have to undergo dialysis in this circumstance. Additional fluid and waste are filtered through the blood during dialysis. Dialysis can help treat renal disease, but it cannot cure it. Depending on your symptoms, a kidney transplant may be another option for treatment. A big contributing factor to ongoing kidney infections is diabetes. High glucose levels are brought on by an illness cluster known as diabetes. Long-term damage to renal veins results from the blood's increased sugar content. This suggests that the kidneys are unable to properly purify the blood. When your body is overloaded with toxins, kidney disappointment might occur [2]. Another common kidney problem is kidney stones. They occur when minerals and other chemicals in the blood form solid masses in the kidneys (stones). Kidney stones often pass through the body while urinating. Although passing kidney stones might be extremely challenging, they rarely present serious problems [3]. A kidney tumor, often known as carcinoma, is an unusual growth. Some kidney tumors are harmful, whereas others are benign (not cancerous) (dangerous). Renal tumors can occur, however, one in four are benign. More subdued crowds will inevitably be safe. Larger masses will inevitably be destructive. Some growths may take longer protectest than others, and some may even be aggressive. Aggressive cancers quickly form, grow, and spread. Conditions that damage your kidneys and reduce their ability to keep you healthy by removing waste from your blood are included in chronic kidney infections. Wastes can build up to considerable levels in your blood and make you feel exhausted if renal disease worsens. You could have complications such as high blood pressure, illness (low blood count), brittle bones, inadequate nutrition, and nerve damage [4].

1.2 Problem Statement

Many people show little interest in their excellent well-being. They consume various types of unhealthy food and suffer the negative repercussions of various complex illnesses. Due to the weakness of their immune systems, older people are more susceptible to the virus. Eating a variety of unhealthy food types can cause renal disease. It doesn't matter how effectively the body's blood is cleansed; many diseases might thrive in the kidneys and develop there due to diabetes, hypertension, and other blood pressure disorders. Kidney disease affects 50% of older people in Bangladesh. In my research paper, I discussed the most effective way to identify various stages of kidney disease, such as kidney stones, tumors, and cysts.

1.3 Research Objectives

a) To find out which deep learning algorithms are worked best for kidney disease data classification.
b) To identify the best model for classification.
c) To use a simple machine vision-based strategy to increase the precision of classifying them.

1.4 Research Questions

a) How can we easily diagnose kidney disease using any method?
b) Which deep learning algorithm can be used to complete the investigation gaps very easily?
c) How can we increase prediction accuracy through deep learning algorithms?

1.5 Report Layout

Chapter 1 presents the research introduction, objectives, and key research questions.
Chapter 2 highlights a detailed review of the related literature.
Chapter 3 describes the proposed methodology with a detailed description.
Chapter 4 explains the result analysis and comparison with existing work.
Chapter 5 concludes the present research along with a direction for future work.

CHAPTER 2

Literature Review

2.1 Related works

In the past, a number of researchers have attempted to identify kidney disease using a variety of methodologies, but they have not been successful. For many years, doctors have identified kidney disease by taking experience into account. However, this intuitive approach has relatively little accuracy. Therefore, it is not a reliable method for determining if kidney disease is present or not. Additionally, this method is dependent on people's background knowledge. In order to achieve a high recognition precision rate, people receive a lot of background information and skills. Otherwise, it has a poor exactness rate.

S. Gopika [5] proposed Chronic kidney disease is an aging problem in the current growing population. Kidney disease surveillance and prediction is very important for patients to provide adequate and appropriate treatment Data mining can extract interesting patterns for gigantic medical databases. with kidney disease can be automatically analyzed from their disease data taking into account prior unwanted data can be removed to provide useful medical information on a patient. Medical data mining can detect disease patterns and predict severity of a patient's disease. pertinent than probabilistic theories for results as precise results and inferences become a necessity to kidney diseases in patients.

JIONGMING QIN[6] proposed Early detection of CKD enables patients to receive timely treatment to ameliorate the progression of this disease. Machine learning models can effectively aid clinicians to achieve this goal due to their fast and accurate recognition performance. The CKD data set was obtained from the University of California Irvine (UCI) machine learning repository, which has a large number of missing values. After effectively filling out the incomplete data set, six machine learning algorithms (logistic regression, random forest, support vector machine, k-nearest neighbor, naive Bayes classifier and feed-forward neural network) were used to establish models. Among these machine learning models, random forest achieved the best performance with 99.75D44 diagnosis accuracy. By analyzing the misjudgments generated by the established models, we proposed an integrated model that combines logistic regression and random forest by using perceptron, which could achieve an average accuracy of 99.83 Ter ten times of simulation.

F. M. Javed Mehedi Shamrat[7] Chronic kidney disease is the loss of kidney function. Often time, the symptoms of the disease are not noticeable and a significant amount of lives are lost annually due to the disease. Using a machine learning algorithm for medical studies, the disease can be predicted with a high accuracy rate and a very short time. Using four of the
supervised classification learning algorithms, i.e., logistic regression, Decision tree, Random Forest, and KNN algorithms, the prediction of the disease can be done. In the paper, the performance of the predictions of the algorithms is analyzed using a pre-processed dataset. The performance analysis is done base on the accuracy of the results, prediction time, ROC and AUC Curve, and error rate. The comparison of the algorithms will suggest which algorithm is the best fit for predicting chronic kidney disease.

Guanyu Yang [8] proposed Accurate kidney and tumor segmentation in CT images is a prerequisite step in surgery planning. However, automatic and accurate kidney and renal tumor segmentation in CT images remain a challenge. In this paper, we propose a new method to perform a precise segmentation of kidney and renal tumors in CT angiography images. The proposed network is implemented as an end-to-end learning system directly on 3D volumetric images. These values are higher than those obtained from the other two neural networks.

El-Houssainy A. Rady [9] proposed The results of applying Probabilistic Neural Networks (PNN), Multilayer Perceptron (MLP), Support Vector Machine (SVM) and Radial Basis

Function (RBF) algorithms have been compared, and our findings show that the PNN algorithm provides better classification and prediction performance for determining severity stage in chronic kidney disease.

Wenshuai Zhao [10] Accurate segmentation of kidneys and kidney tumors is an essential step for radiomic analysis as well as for developing advanced surgical planning techniques. In clinical
analysis, segmentation is currently performed by clinicians from the visual inspection of images gathered through a computed tomography (CT) scan. We present a multi-scale supervised 3D U-Net, MSS U-Net to segment kidneys and kidney tumors from CT images.

Kanishka Sharma [11] proposed It is characterized by enlargement of the kidneys caused by progressive development of renal cysts, and thus assessment of total kidney volume (TKV) is crucial for studying disease progression in ADPKD. The proposed method has been trained (n=165) and tested (n=79) on a wide range of TKV (321.2–14,670.7mL) achieving an overall mean Dice Similarity Coefficient of 0.86±0.07 (mean±SD) between automated and manual segmentations from clinical experts and a mean correlation coefficient (ρ) of 0.98 ($p<0.001$) for segmented kidney volume measurements in the entire test set.

2.2 Scope of the Problem

The great majority of years were spent by scientists trying to accurately differentiate renal disease in various ways. The different stages of renal disease have been the subject of several analyses. The majority of doctors have dealt with a couple of steps of kidney disease as well as a few informational indexes. The results weren't considered to be true to form because there wasn't enough information used to make decisions. In the clinical field, numerical data are not always obtained by consistently outstanding results. Because of the use of numerical data, many scientists have achieved little or no precision.

2.3 Challenges

There are some researches challenges focused on this study which are the following:

a) **Image Processing**: Since the picture was gathered from better places, the picture site properties were not right. There was some noise, a few pictures were high or low differentiation. So it was trying to tackle every one of the issues and make an ideal picture.

b) **Deep Learning Algorithm:** Many researchers used machine learning algorithms in their kidney disease detection project. As I used deep learning algorithms it was too critical for me.

c) **Size Change:** The images in the dataset I organized weren't all the same size. I struggled to make sure that all of the images were the same size.

d) **Rotation:** In CT images, kidney images may be seen from any erroneous location, and their appearance may differ when viewed from different points. This requires a grouping framework to be represented.

e) **Time Complexity:** Different analysts have carried out various models for kidney issues. It was trying for me to decrease the time complexity from their time complexity.

f) **Accuracy Improvement:** Another challenge was to improve model accuracy. Many kidney researchers worked on kidney disease. Another challenge was to improve model accuracy. Many kidney researchers worked on kidney disease.

CHAPTER 3
Materials and Methods

3.1 Working Process

To properly complete the entire work, 5 stages are used, and the methods are:

a) Image gathering and prepared dataset
b) Image Pre-processing
c) Apply Deep Learning Algorithm
d) Detecting Disease
e) Result Analysis

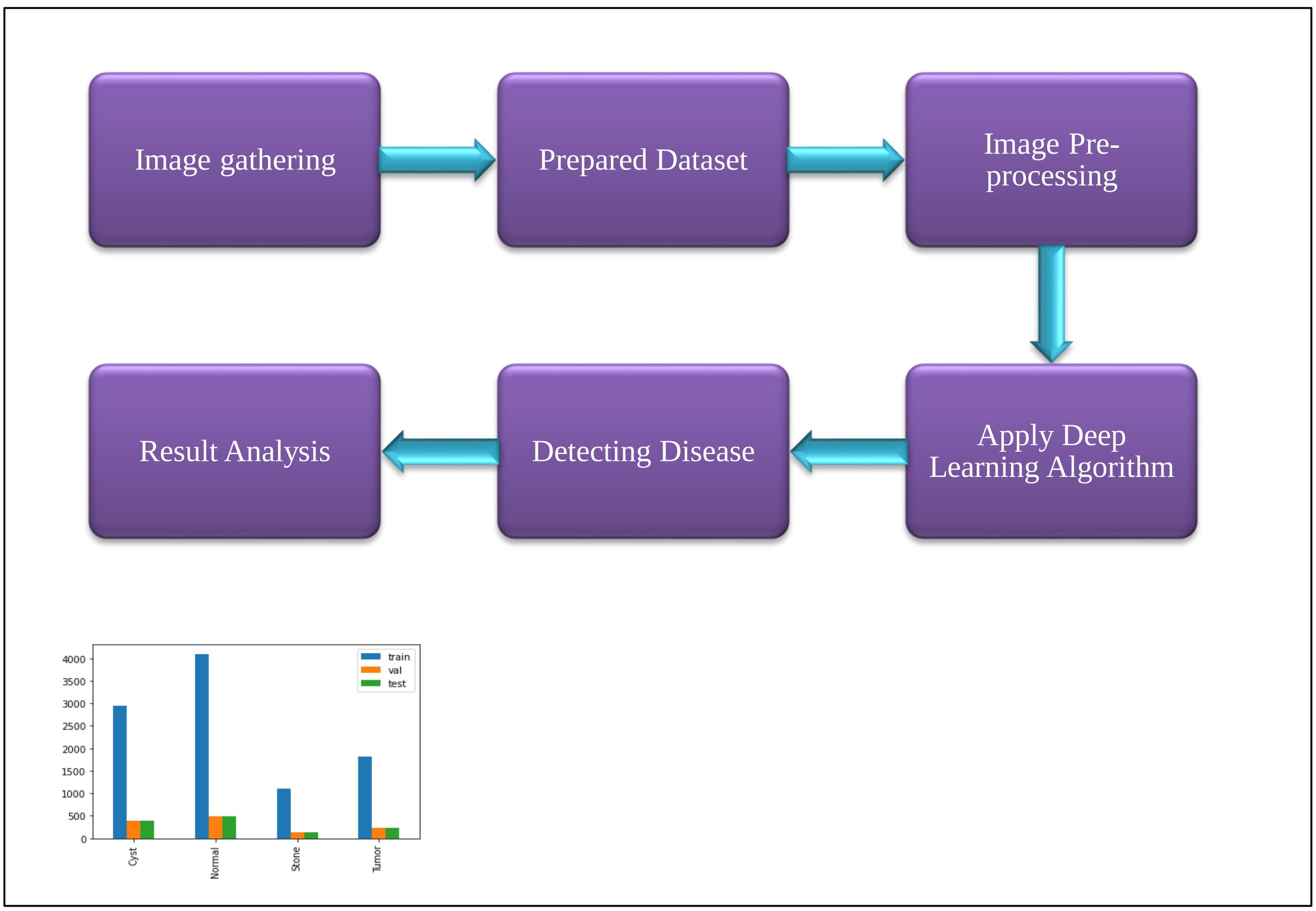

Figure 01: Working process of the model

The total working process starting from image gathering to the result in the analysis is presented in figure 2 and explained elaborately in the following sections.

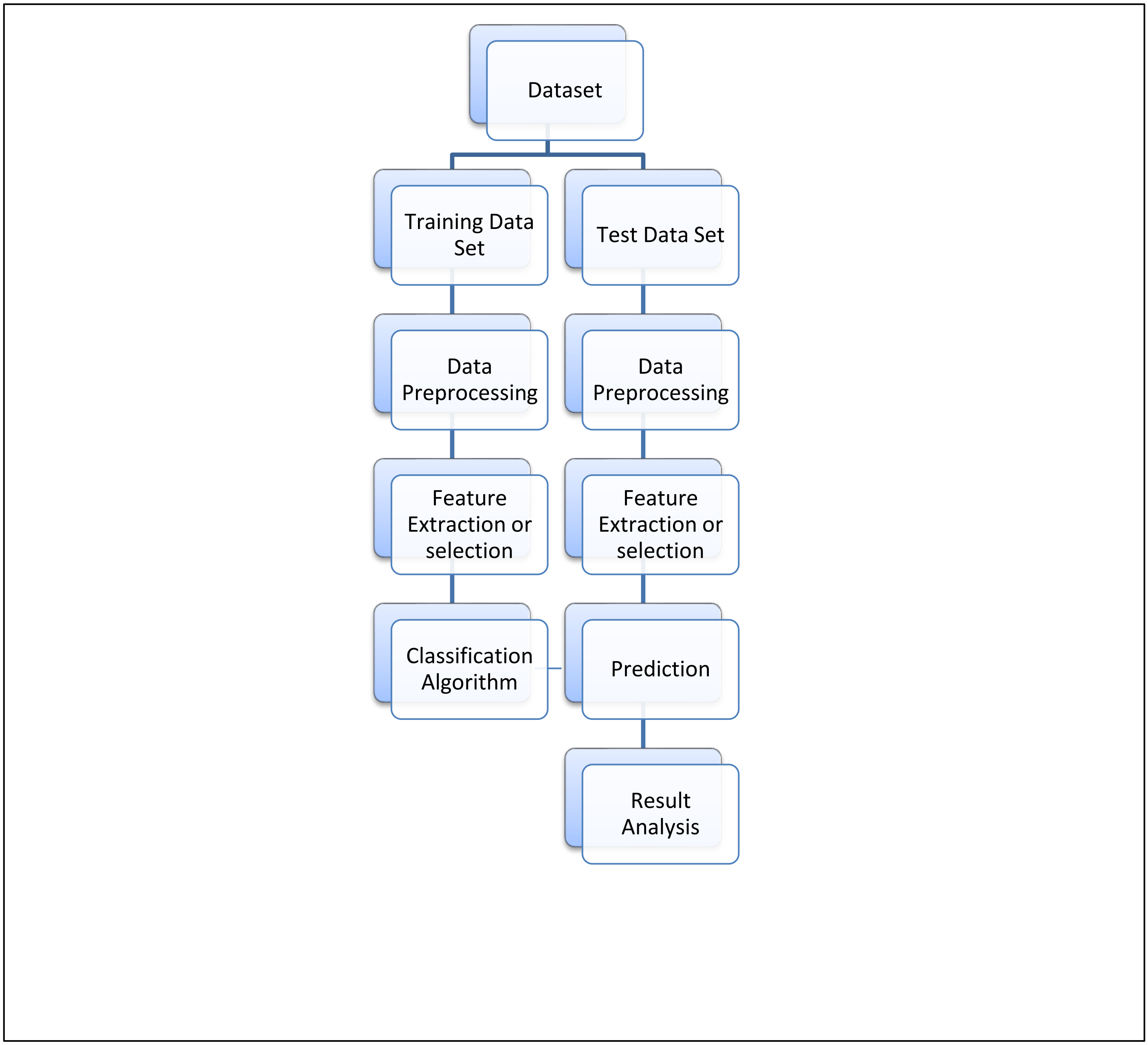

Figure 02: Working process of the proposed model

3.2 Dataset Preparation

This dataset, which I collected, contains 12446 images that I divided into 4 classes. There are 3709 images of the cyst, 1377 images of stones, 2283 images of growth, and 5077 images of solid kidneys across the four groups.

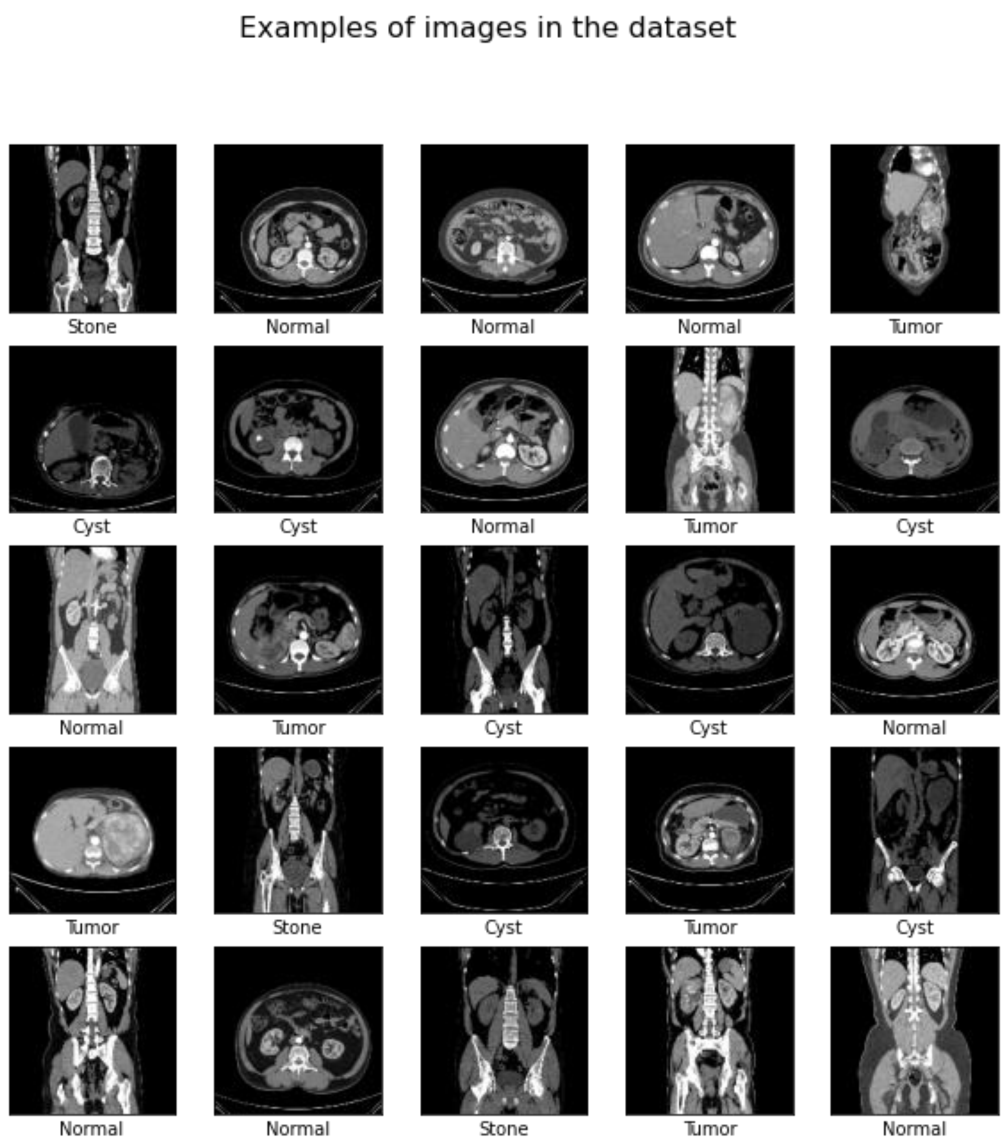

Figure 03: Different Classes of Kidney Disease

The collected images are unsuitable in terms of size and variety, and some are loud. To improve the picture quality, even more, the CLAHE technique was utilized. The model was supposed to be prepared using a sizable dataset, but the data that was actually collected was inadequate. Thus, the overfitting problem arises, and several information augmentation tactics, such as pivot, interpretation, scaling, and shearing, were used to address it.

3.3 Image Pre-processing

Prior to being utilized for model preparation and surmising, the image should initially go through image preprocessing. This incorporates, however, isn't restricted to, changes in accordance with the size, orientation, and color. The motivation behind pre-handling is to raise the image quality so we can analyze it all the more successfully. Preprocessing permits us to dispose of undesirable contortions and further develop explicit characteristics that are fundamental for the application we are chipping away at. Those attributes could change relying on the application. A picture should be preprocessed for the product to work accurately and produce the ideal outcomes. Convolutional neural networks completely associated layers requested that every one of the pictures is in varieties of a similar size and for this image preprocessing is necessary. If the information photos are unusually large, reducing their size will significantly reduce the amount of time needed to construct the model without fundamentally affecting model execution. Although mathematical modifications of images (such as rotation, scaling, and translation are organized as pre-handling strategies, the goal of pre-handling is an improvement of the image information that smothers unintentional mutilations or upgrades some picture highlights necessary for ensuing handling.

3.3.1 Image Enhancement Technique

For many real vision frameworks, image enhancement and reproduction are the basic handling phases. Their goal is to investigate the visual aspects of images and provide credible evidence for any ensuing visual independent direction. Study topics include generative countermeasure networks, remaining neural networks, and convolution neural network organizations. A flexible helper age network is provided as part of a rain fog image enhancing generative countermeasure network model. The intermittent consistency misfortune and sporadic perceptual consistency misfortune examinations are offered, and the objective misfortune capability is described. Examining the central problem of picture layering, a layering layout method with a substantial extension structure is suggested. This method recognizes completing numerous duties using flexible element understanding, which has a respectable level of hypothetical assurance. [14] This study could not only provide viewers with a pleasant visual experience at any time but also contribute to improving how PC vision apps are presented. The nature of low-light images can be significantly improved by picture upgrading innovation, resulting in a picture with better definition, more extravagant surface nuances, and lower picture clamor. In this study, we used an enhancement technique and was histogram equalization. The method of equalizing the histogram is sometimes referred to as a "grayscale modification for contrast upgrade." The entering phases might be effectively dispersed over the entire infiltrating measure using this approach. Since the resulting image's histogram is often level, histogram modification could produce an outcome that is worse than the original image. A dull district might produce enormous tops in the histogram. Accordingly, histogram equalization may encourage a longer deception of irritating image commotions. This implies that it doesn't adhere to the neighborhood contrast requirement; modest separation differences can generally be discarded after the number of pixels dimming in a given dull reach is at or almost at zero. In this procedure, an image is divided into smaller images or squares, and each smaller image or square is given a histogram balance. By that time, isolating or bilinear interference has limited the ability of artifacts to inhibit joining blocks.

3.3.2 Contrast Limited Adaptive Histogram Equalization

An improvement of the versatile histogram condition (AHE), contrast restricted versatile histogram balance (CLAHE) adds to further developing difference in the picture by widening the picture's power range or carrying out a loosening up component at the picture's most successive force esteem. Contrasted with AHE, CLAHE was an improvement. Utilizing the CLAHE strategy, an image is partitioned into tiles or intelligent segments. Each consistent region's histogram is made, and removing is conveyed in foreordained regard. The histogram compartments are split again as indicated by the cut aggregate. This histogram is the principal histogram's changed kind. This approach diminishes the issue of over-progress and addresses the edge-shadowing impact of AHE. CLAHE has shown progress in working on clinical pictures with restricted qualifications. Cut histogram imperative and size of the set focused region are the boundaries that ought to be thought about for CLAHE. The CLAHE yield might be impacted by these limits. By revamping the utilized faint attributes, this strategy makes stowed-away parts of the picture more self-evident.

3.5 Deep Learning

Machine learning, which at its core is a neural network with three or more layers, includes deep learning as a subset. These neural networks attempt to replicate how the human brain works, but they are unable to match it, allowing it to "learn" from enormous amounts of data. Additional hidden layers can assist to tune and improve for accuracy even if a neural network with only one layer can still produce approximation predictions. These algorithms can handle text and visual data that is unstructured and automate feature extraction, reducing the need for human expertise.

By using data inputs, weights, and bias, artificial neural networks, often referred to as Deep Learning Neural Networks (DNN), attempt to imitate the functioning of the human brain. DNNs are made up of several layers of linked nodes, each of which improves on the prediction or classification made by the layer before it. Forward propagation refers to the movement of calculations through the network. A deep neural network's observable layers are its input and output layers. The deep learning model ingests the data for processing in the input layer, and the final prediction or classification is performed in the output layer.

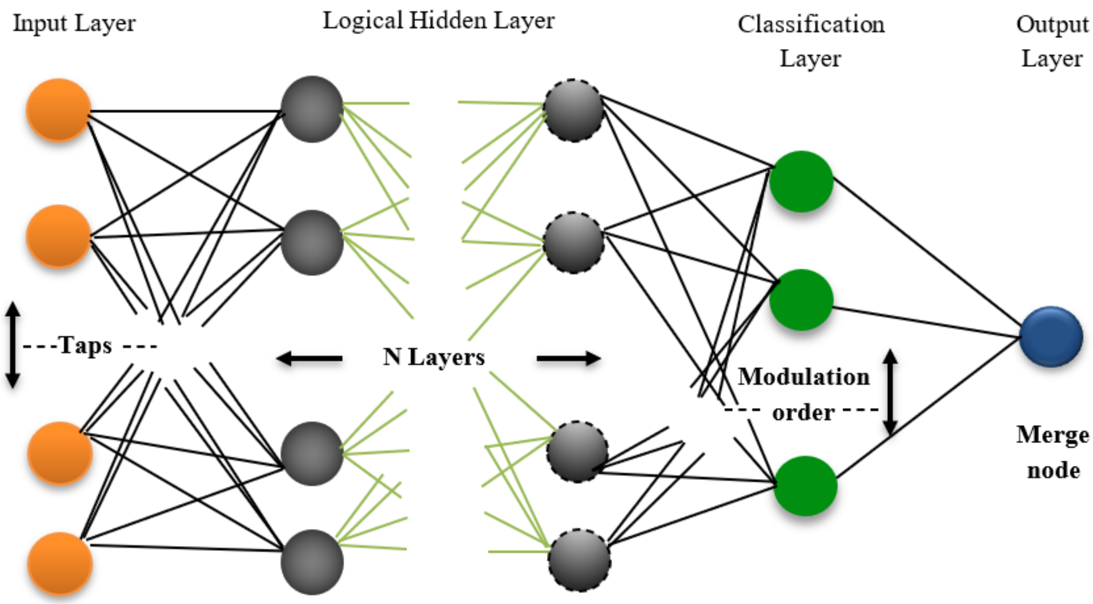

Figure 04: Architecture of Deep Learning Neural Network

3.5 Convolutional Neural Network

CNN is a type of deep learning model for managing information with a matrix design, such as images. CNN is inspired by the association of the creature's visual cortex and was designed to afterwards and adaptively learn the spatial pecking orders of elements, from low-to undeniable level instances. Convolution, pooling, and fully linked layers are the three types of layers (or building blocks) that make up CNN on a regular basis. Highlight extraction is carried out by the first two layers—convolution and pooling—while the third layer—a completely associated layer—maps the separated parts into the final outcome, such as grouping. In CNN, which is composed of numerous numerical operations like convolution, a particular type of direct activity, a convolution layer plays an important role. [12] The pixel values in computerized images are stored in a two-layered (2D) matrix, and a small matrix of boundaries known as the kernel, an optimizable feature extractor, is applied at each picture position, making CNN extremely adept at handling pictures because an element could appear anywhere in the image. Extracted items may gradually and dynamically grow more confusing as one layer deals with the effects of its actions in the subsequent layer. Preparing is the most popular method of upgrading boundaries, such as bits, and it is carried out to reduce the contrast between the results and the names of the ground truth using advancement calculations like slope plummet and back propagation, among others.

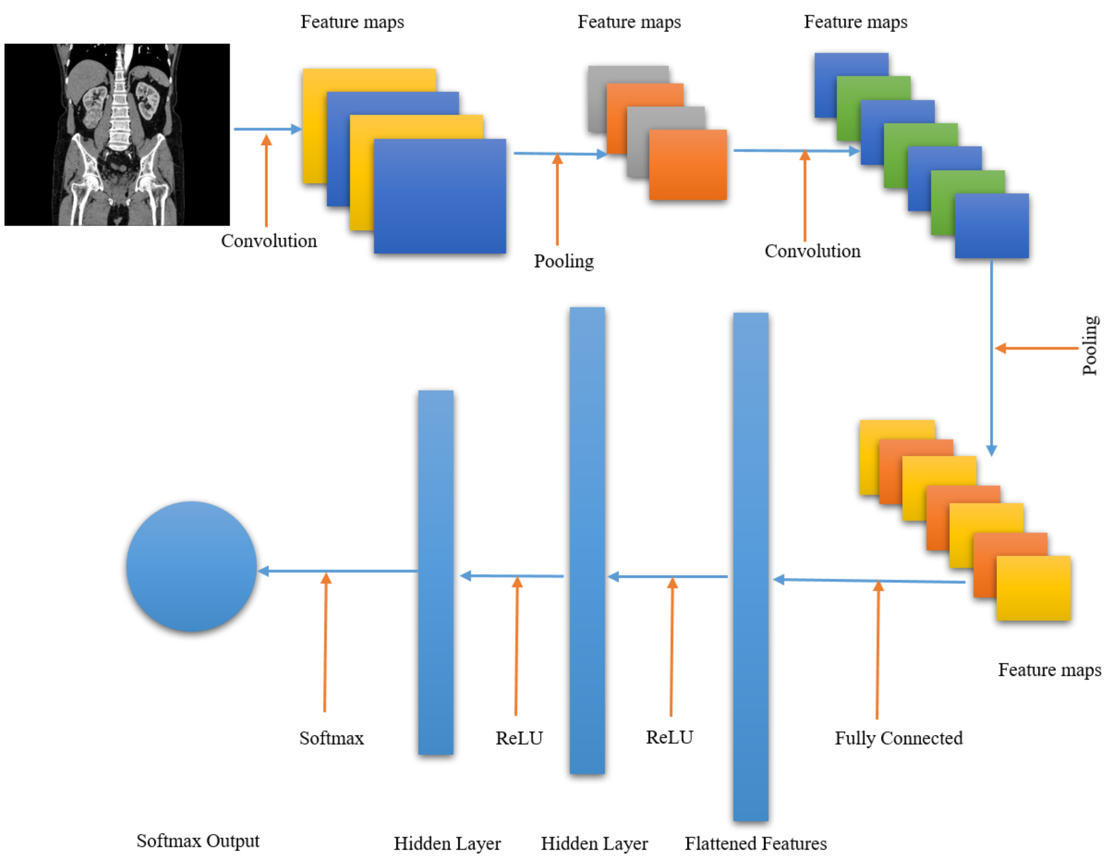

Figure 05: Architecture of Convolutional Neural Network.

3.5.1 Convolutional Layer

The convolutional layer plays an important role in CNN's operation. This procedure is repeated by applying multiple kernels to form an arbitrary number of feature maps, which represent different characteristics of the input tensors; different kernels can, thus, be considered different feature extractors. The convolution operation described above does not allow the center of each kernel to overlap the outermost element of the input tensor, ad reduces the height and width of the output feature map compared to the input tensor. Padding, typically zero padding, is a technique to address this issue, where rows and columns of zeros are added on each side of the input tensor, so as to fit the center of a kernel on the outermost element and keep the same in-plane dimension through the convolution operation. Modern CNN architectures usually employ zero padding to retain in-plane dimensions in order to apply more layers. Without zero padding, each successive feature map would get smaller after the convolution operation. The distance between two successive kernel positions is called a stride, which also defines the convolution operation. Weight sharing creates the following characteristics of convolution operations: (1) letting the local feature patterns extracted by kernels translation b invariant as kernels travel across all the image positions and detect learned local patterns, (2) learning spatial hierarchies of feature patterns by downsampling in conjunction with a pooling operation, resulting in capturing an increasingly larger field of view, and (3) increasing model efficiency by reducing the number of parameters to learn in comparison with fully connected neural networks. Kernels are the only parameters automatically learned during the training process in the convolution layer; on the other hand, the size of the kernels, number of kernels, padding, and stride are hyperparameters that need to be set before the training process starts.

The following equation is used for this calculation:

$$\frac{(V - R) + 2Z}{S + 1}$$

Here, V stands for e input size of the volume such as height × width × depth, R and Z stand for the accessible field size, and the volume of zero padding is set separately. S denoting to the stride. If the premeditated outcome from this equation isn't equivalent to an entire number formerly the stride has been inaccurately fixed, since the neurons will be not able to fix perfectly through the prearranged input.

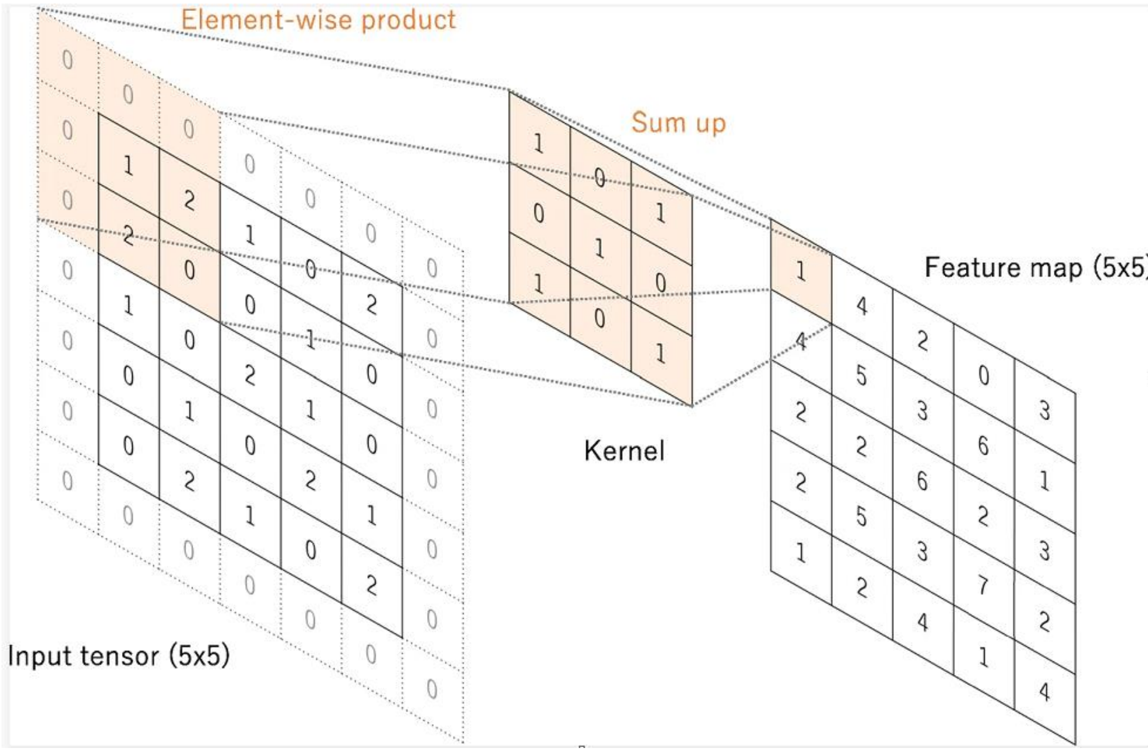

Figure 06: A 5x5x1 image convolved with a 3x3x1 kernel to become a 3x3x1 convolved feature.

3.5.2 Pooling Layer

A pooling layer gives a normal down-sampling activity which lessens the in-plane dimensionality of the component maps to acquaint an interpretation invariance with little moves and twists, and reduction the quantity of ensuing learnable boundaries. It is important that there is no learnable boundary in any of the pooling layers, though channel size, step, and cushioning are hyperparameters in pooling tasks, like convolution activities. The pooling Layer has two types:

(i) Max Pool Layer

(ii) Global Average Pool Layer

3.5.2.1 Max Pool Layer

The pooling layer's main objective is to dynamically reduce the exhibition's dimensionality while also reducing the number of boundaries and the computational unpredictability of the model.

The pooling layer applies to each actuation plot in the data and uses the "Maximum" capacity to measure its dimensionality. The most effective CNN’s start with the technique of max-pooling layers along with parts of dimensionality of 2 2 spread with a step of 2 horizontally the spatial components of the information. As the profundity size is supported to its standard size, the action's initiation plot is depressed to 25% of the noteworthy size.

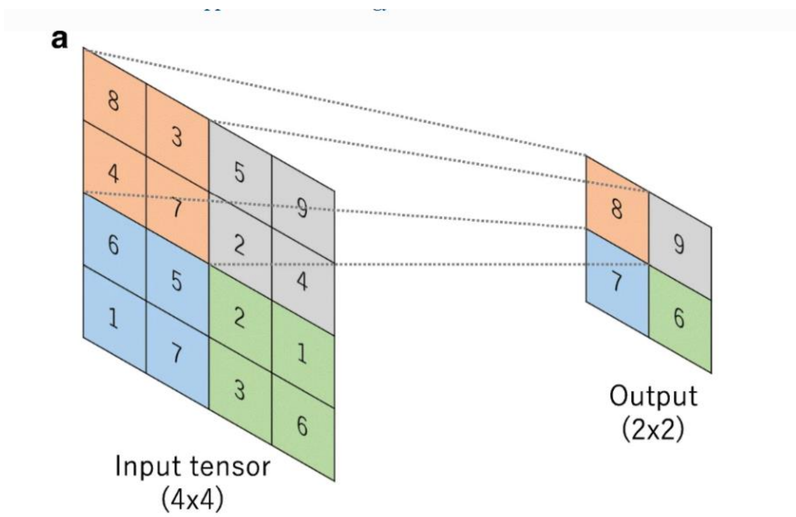

Figure 07: Representation of Max Pooling Layer with Hyperparameters 2 X 2 filters and Stride size 2

There are only two widely used methods for maximum pooling due to the pooling layer's terrible behavior. The step and channels of pooling layers are often both fixed to 2 2, allowing the layer to spread out over the entire spatial dimensions of the data. Anywhere the step is fixed to 2 through a bit size fix to 3 should use covered pooling instead. Consuming a chunk that is higher than three will frequently practically prevent the original from being displayed because of the harmful way that pooling behaves. It is simple to understand that CNN designs may contain universal pooling beyond max-pooling. Pooling neurons that can perform a wide range of conventional approaches, such as L1/L2-standardization and regular pooling, are included in general pooling layers.

3.5.2.2 Global Average Pool Layer

There are only two widely used methods for maximum pooling due to the pooling layer's terrible behavior. The step and channels of pooling layers are often both fixed to 2 2, allowing the layer to spread out over the entire spatial dimensions of the data. Anywhere the step is fixed to 2 through a bit size fix to 3 should use covered pooling instead. Consuming a chunk that is higher than three will frequently practically prevent the original from being displayed because of the harmful way that pooling behaves.

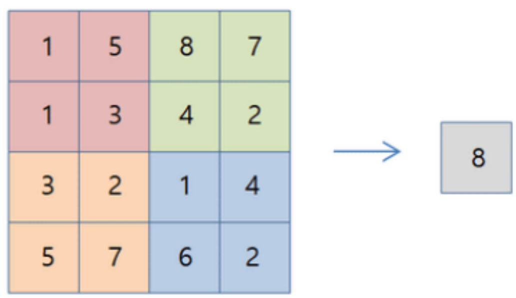

Figure 08: Representation of Global Avearge Pooling Layer with Hyperparameters 2 X 2 filters

3.5.3 Fully Connected Layer

The result highlight guides of the last convolution or pooling layer are commonly leveled, i.e., changed into a one-layered (1D) exhibit of numbers (or vector), and associated with at least one completely associated layer, otherwise called thick layers, in which each info is associated with each result by a learnable weight. When the highlights removed by the convolution layers and downsampled by the pooling layers are made, they are planned by a subset of completely associated layers to the last results of the organization, for example, the probabilities for each class in order errands. The last completely associated layer commonly has a similar number of result hubs as the number of classes. Each completely associated layer is trailed by a nonlinear capability, like ReLU, as depicted previously.

3.6 Transfer Learning

In transfer learning, the knowledge of an already trained machine learning model is applied to a different but related problem. For example, if you trained a simple classifier to predict whether an image contains a backpack, you could use the knowledge that the model gained during its training to recognize other objects like sunglasses. Transfer learning is mostly used in computer vision and natural language processing tasks like sentiment analysis due to the huge amount of computational power required. Nevertheless, it has become quite popular in combination with neural networks that require huge amounts of data and computational power. In computer vision, for example, neural networks usually try to detect edges in the earlier layers, shapes in the middle layer, and some task-specific features in the later layers.
Let`s go back to the example of a model trained for recognizing a backpack on an image, which will be used to identify sunglasses. In the earlier layers, the model has learned to recognize objects, because of that we will only retain the latter layers so it will learn what separates sunglasses from other objects.

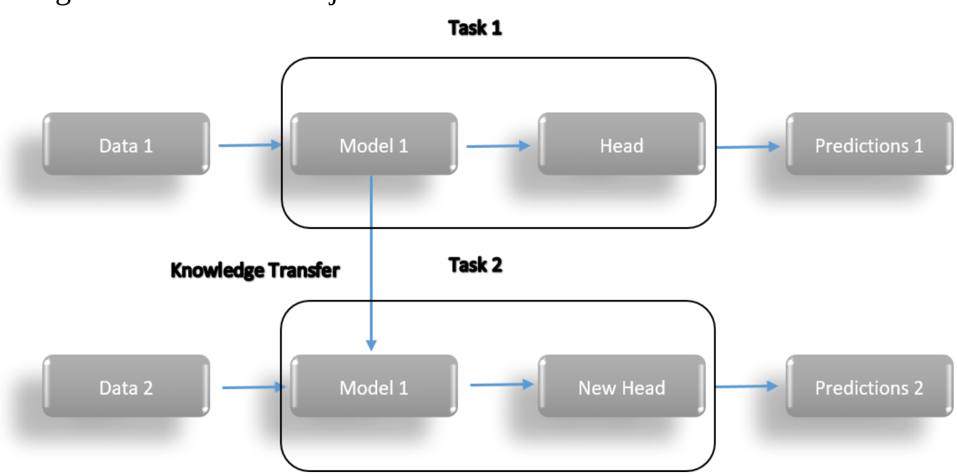

Figure 09: Architecture of Transfer Learning

3.7 VGG16

The input to any of the network configurations is considered to be a fixed size 224 x 224 image with three channels – R, G, and B. The only pre-processing done is normalizing the RGB values for every pixel.
Image is passed through the first stack of 2 convolution layers of the very small receptive size of 3 x 3, followed by ReLU activations. This configuration preserves the spatial resolution, and the size of the output activation map is the same as the input image dimensions. The activation maps are then passed through spatial max pooling over a 2 x 2-pixel window, with a stride of 2 pixels. Thus the size of the activations at the end of the first stack is 112 x 112 x 64. This is followed by the third stack with three convolutional layers and a max pool layer. of filters applied here are 256, making the output size of the stack 28 x 28 x 256. This is followed by two stacks of three convolutional layers, with each containing 512 filters. The output layer is followed by the Softmax activation layer used for categorical classification.

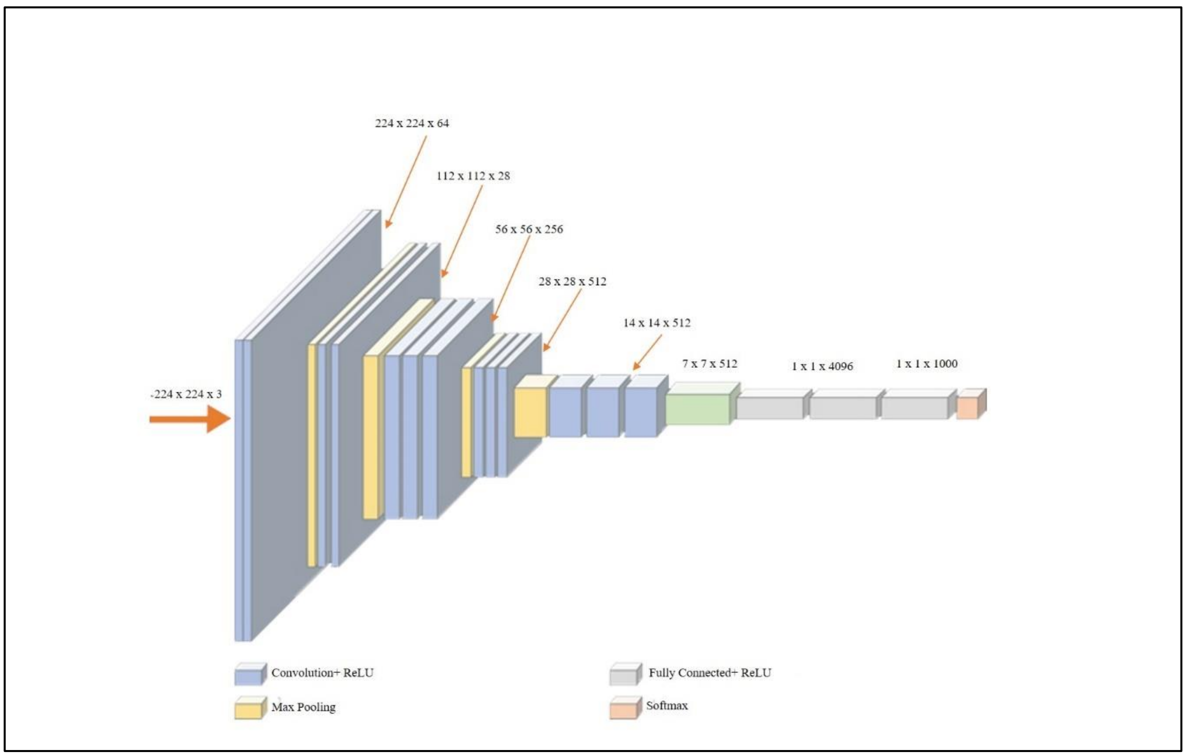

Figure 10: Architecture of Visual Geometric Group (VGG16)

3.8 Resnet34

The convolutional neural network ResNet (Residual Network) popularized the ideas of skip connections and residual learning. Due to this, significantly deeper models may be trained. ResNet model pre-trained at 224x224 resolution on ImageNet-1k. The first ResNet architecture was the Resnet-34 (find the research paper here), which involved the insertion of shortcut connections in turning a plain network into its residual network counterpart. In this case, the plain network was inspired by VGG neural networks (VGG-16, VGG-19), with the convolutional networks having 3×3 filters. However, compared to VGGNets, ResNets have fewer filters and lower complexity. The shortcut connections were added to this plain network. While the input and output dimensions were the same, the identity shortcuts were directly used. The first was that the shortcut would still perform identity mapping while extra zero entries would be padded for increasing dimensions.

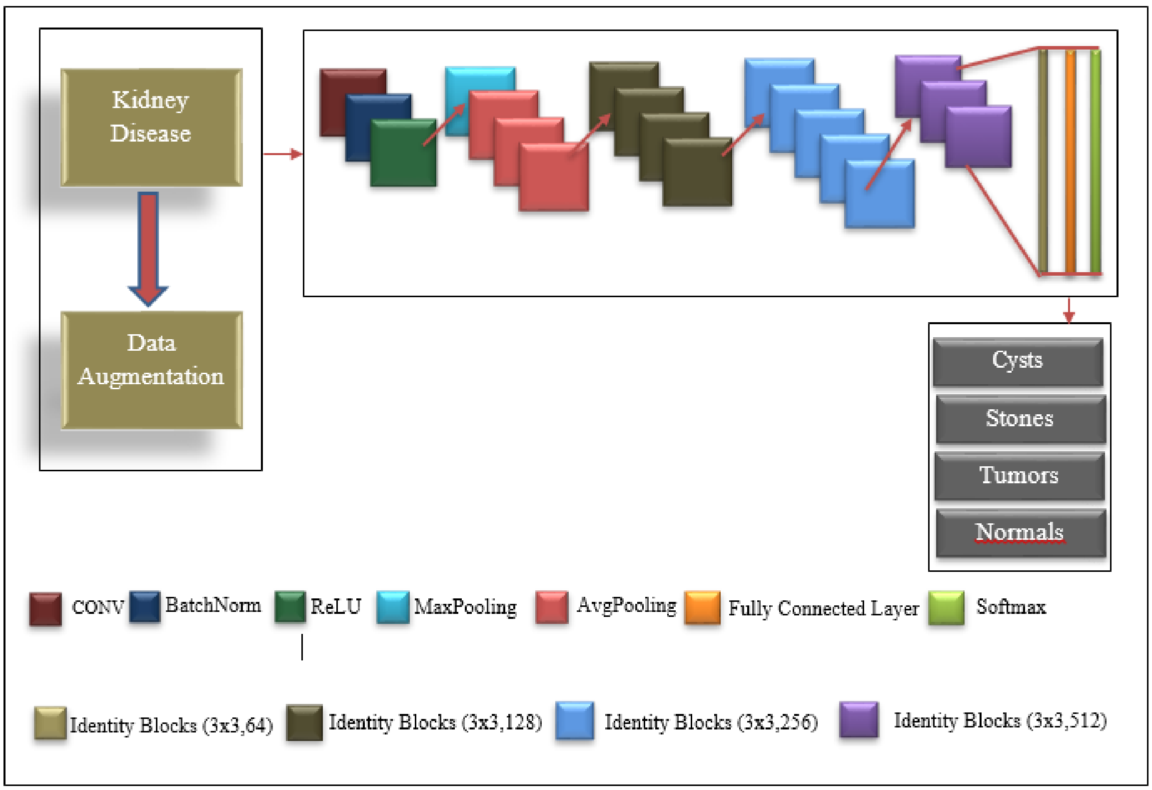

Figure 11: Architecture of ResNet34

3.9 DenseNet201

Because it does not train redundant feature maps, DenseNet, which is short for Dense Convolutional Network, requires fewer parameters than a traditional CNN. DenseNet has relatively few layers—12 filters—which results in the addition of a smaller number of new feature maps. The four variations of DenseNet are DenseNet121, DenseNet169, DenseNet201, and DenseNet264. For the purpose of detecting kidney disease in this study, we utilized DenseNet201 . The original input image and gradients from the loss function are directly accessible to each layer in DenseNet (as depicted in Figure) during training. Therefore, DenseNet is a better option for picture classification because the computational cost was greatly lowered.

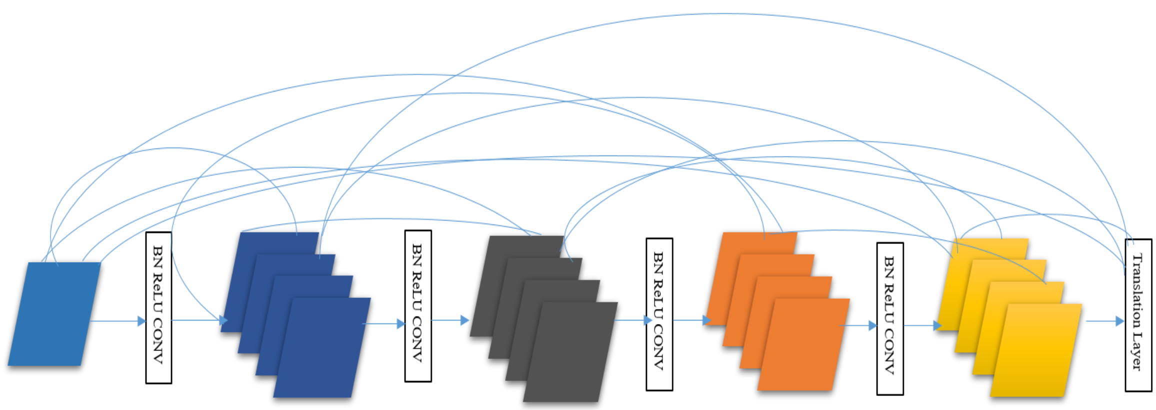

Figure 12: Architecture of DenseNet201

3.10 EfficientNetB1

EfficientNet is an engineering and scaling technique for convolutional neural networks that consistently scales all profundity/width/goal components using a compound coefficient. The EfficientNet scaling technique reliably scales network breadth, profundity, and purpose with a number of preset scaling coefficients, in contrast to a normal practice that scales these variables at random. EfficientNetB1 was engineered using MBConv as a key building piece. As shown, the general engineering can be divided into seven blocks. Each MBConv X block's associated channel size is shown on the screen.

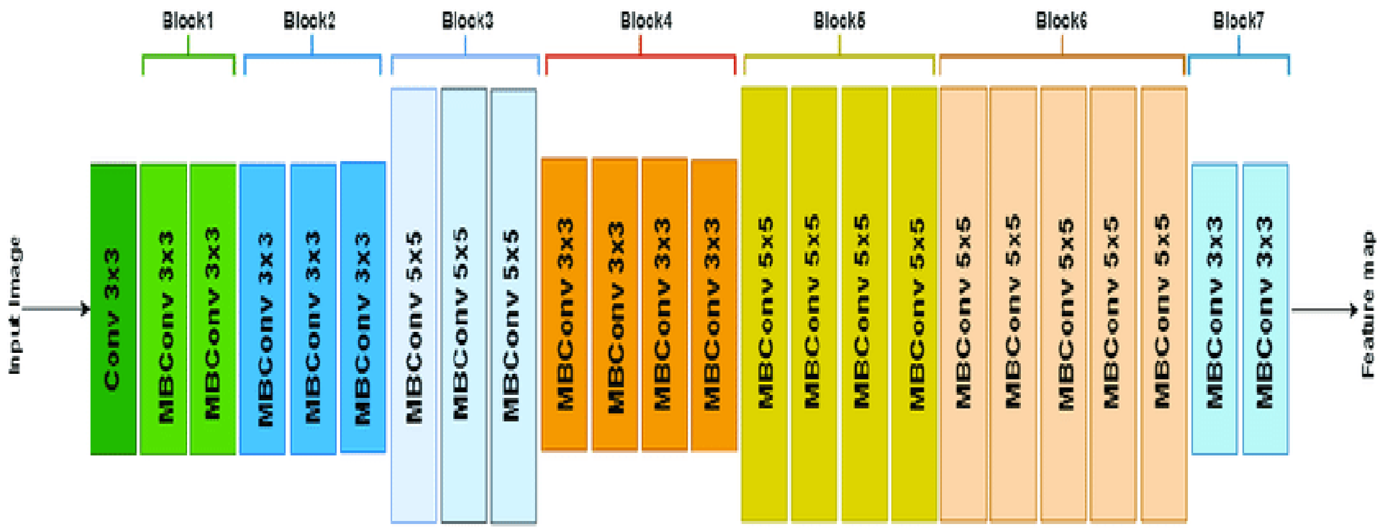

Figure 13: Architecture of EfficientNetB1

3.11 Training and Testing

The dataset which I utilized in my research contains 22446 CT check pictures and the entire dataset is separated into 2 sections. One section is training and the other part is testing. The dataset contains 4 classes and these are cysts, stones, tumors, and normals. The dataset was divided at random, with 80% of the images being used for training and the remaining 20% being used for validation. The calculation is prepared to utilize the picture elements of the preparation set. At last, picture elements of the testing set are utilized for evaluating the exhibition of the model. The programming language utilized is Python with the execution of the accompanying libraries: NumPy, pandas, matplotlib, TensorFlow, scikit-learn, scikit-picture and xgboost. Every model was created using an exchange learning method, and the loss function shown in condition was unmitigated cross-entropy. At 0.001, the learning rate was set.

$$L_{CE} = -\sum_{i=1}^{n} t_i \log(p_i) \quad (1)$$

All of the designs shown in condition were activated using the SoftMax feature of Adam's streamlining agent.

$$\mathrm{fi}(\overrightarrow{a}) = \frac{e^{a_i}}{\sum_k e^{a_k}} \tag{2}$$

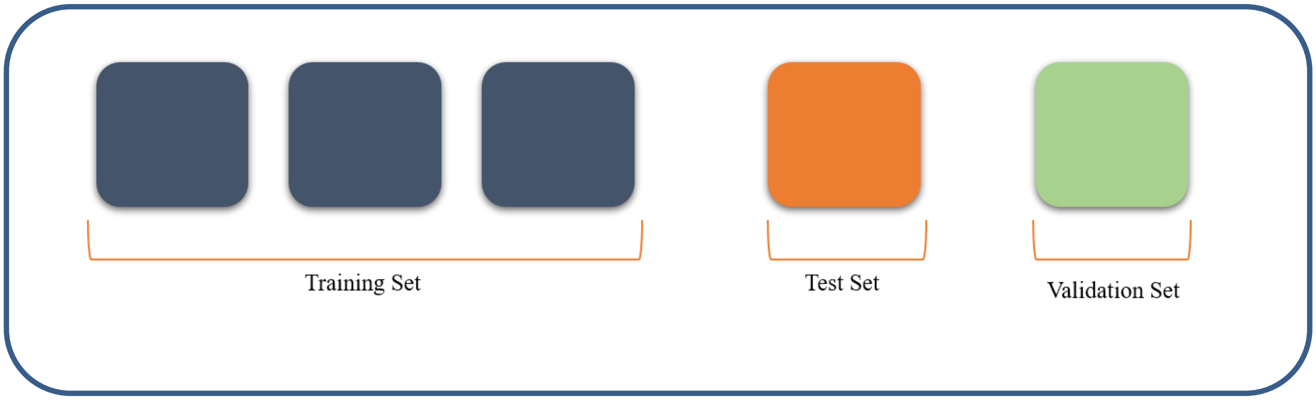

Figure 14: Architecture of Proportion

Table I: Distribution of Kidney Dataset

Dataset	**Cysts**	**Stone**	**Tumor**	**Normal**
Train Dataset	**2968**	**1102**	**1831**	**4062**
Test Dataset	**370**	**137**	**229**	**508**
Validation Dataset	**370**	**137**	**229**	**508**

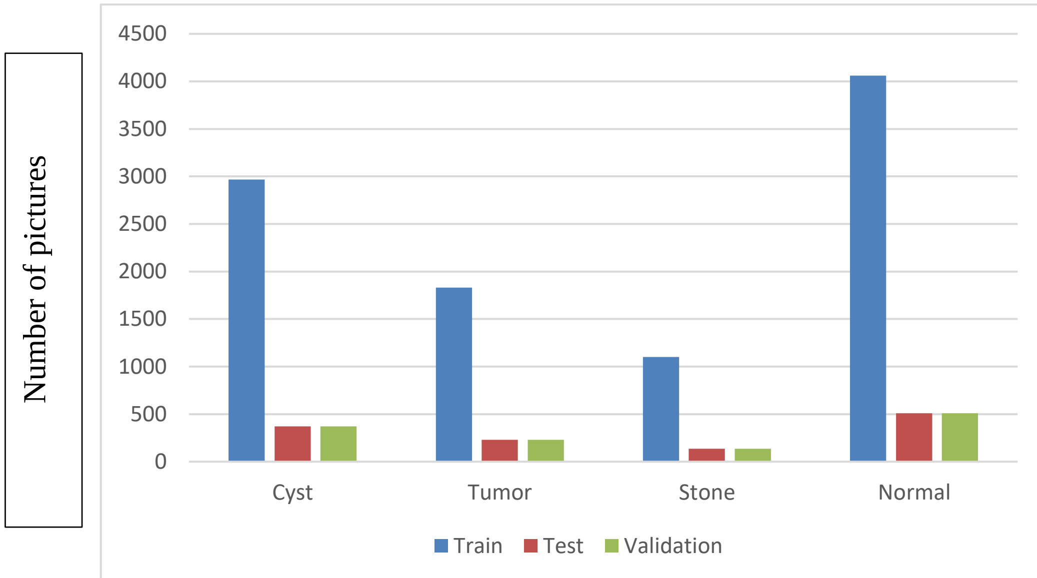

Figure 15: Distribution of Dataset

CHAPTER 4
Experimental Results and Discussion

4.1 Results and Discussion

To find renal illness, we applied deep learning. Using CNN architecture, we were able to detect diseases. In this experiment, we additionally make use of the VGG16, ResNet34, DenseNet201, and EfficientNetB1 CNN architectures. The best accuracy was reached by VGG16 at 99%, followed by ResNet34 at 63%, DenseNet201 at 90%, and EfficientNetB1 at 75%. We provide multiple approaches and confusion measures to evaluate the test's validity. The true positive, true negative, false positive, and false negative values are contained in the confusion matrices. To assess the model's precise prediction, the values are located in the confusion matrix's diagonal location. Based on the confusion matrices, the following equation is used to determine Accuracy, Recall, Precision, and the F1 Score.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{3}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{4}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5}$$

$$\text{F1 Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \tag{6}$$

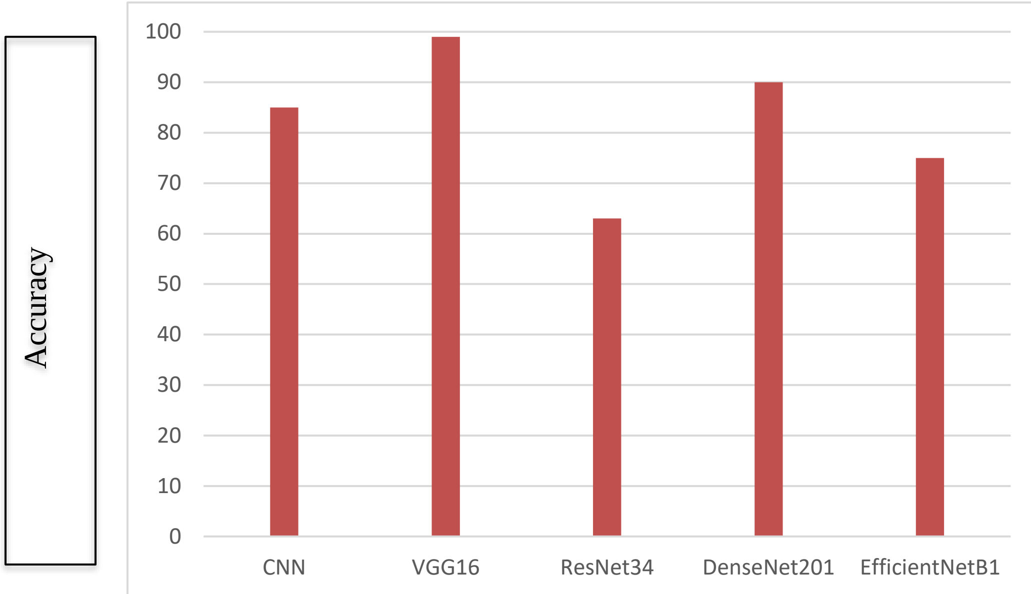

Figure 16:Test Accuracy of Different Transfer Learning Architecture

4.2 Performance Metrics:

To evaluate the performance or quality of the model, different metrics are used, and these metrics are known as performance metrics or evaluation metrics. Each deep learning model aims to generalize well on unseen/new data, and performance metrics help determine how well the model generalizes on the new dataset. To evaluate the performance of a classification model, different metrics are used, and some of them are as follows:

- Accuracy
- Confusion Matrix
- Precision
- Recall
- F-Score
- AUC (Area Under the Curve)-ROC

Accuracy: The accuracy metric is one of the simplest Classification metrics to implement, and it can be determined as the number of correct predictions to the total number of predictions.

Precision: The precision metric is used to overcome the limitation of Accuracy. The precision determines the proportion of positive prediction that was actually correct. It can be calculated as the True Positive or predictions that are actually true to the total positive predictions (True Positive and False Positive).

Recall: It is also similar to the Precision metric; however, it aims to calculate the proportion of actual positive that was identified incorrectly. It can be calculated as True Positive or predictions that are actually true to the total number of positives, either correctly predicted as positive or incorrectly predicted as negative (true Positive and false negative).

F1 score: F1 Score is a metric to evaluate a binary classification model on the basis of predictions that are made for the positive class. It is calculated with the help of Precision and Recall. It is a type of single score that represents both Precision and Recall. So, the F1 Score can be calculated as the harmonic mean of both precision and Recall, assigning equal weight to each of them.

Table II: Performance Metrics

Architectures	**Accuracy (avg)**	**Precision (avg)**	**Recall (avg)**	**F-1 score (avg)**
CNN	.85	.85	.88	.83
VGG16	.99	.99	.99	.99
ResNet34	.63	.55	.44	.55
DenseNet201	.90	.88	.75	.88
EffieientNetB1	.75	69	70	69

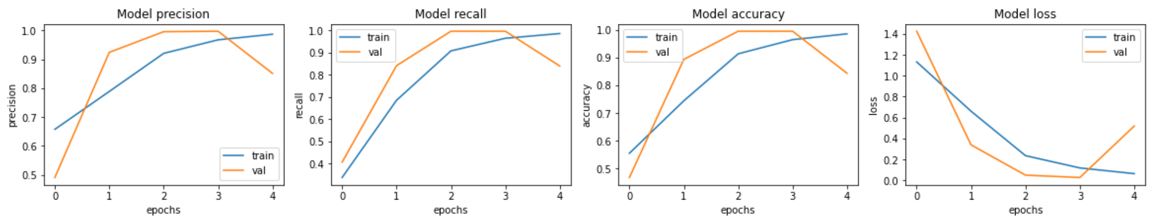

Figure 17: Performance Metrics

4.3 Confusion Metrics

A confusion matrix is a tabular representation of prediction outcomes of any binary classifier, which is used to describe the performance of the classification model on a set of test data when true values are known.

(i) Convolution Neural Network (CNN)

After applying the CNN algorithm on the dataset we find that there are 280 cysts detected, 311 normal or healthy kidney detected, 289 stone detected and 273 tumor detected.

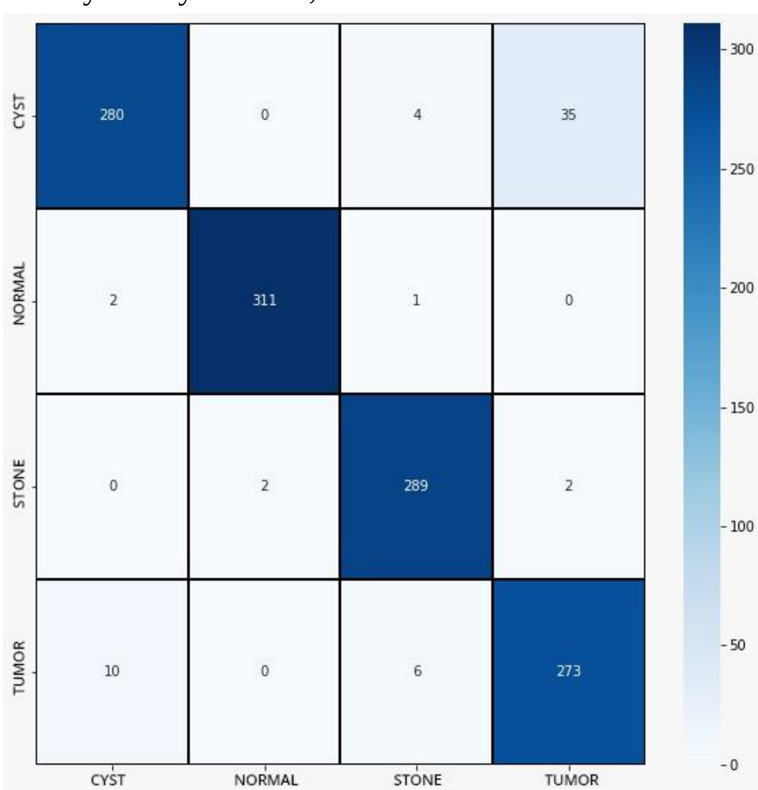

Figure 18: Convolution Neural Network

(ii) VGG16

After applying the VGG16 algorithm on the dataset we find that there are 391 cysts detected, 493 normal or healthy kidney detected, 136 stone detected and 391 tumor detected.

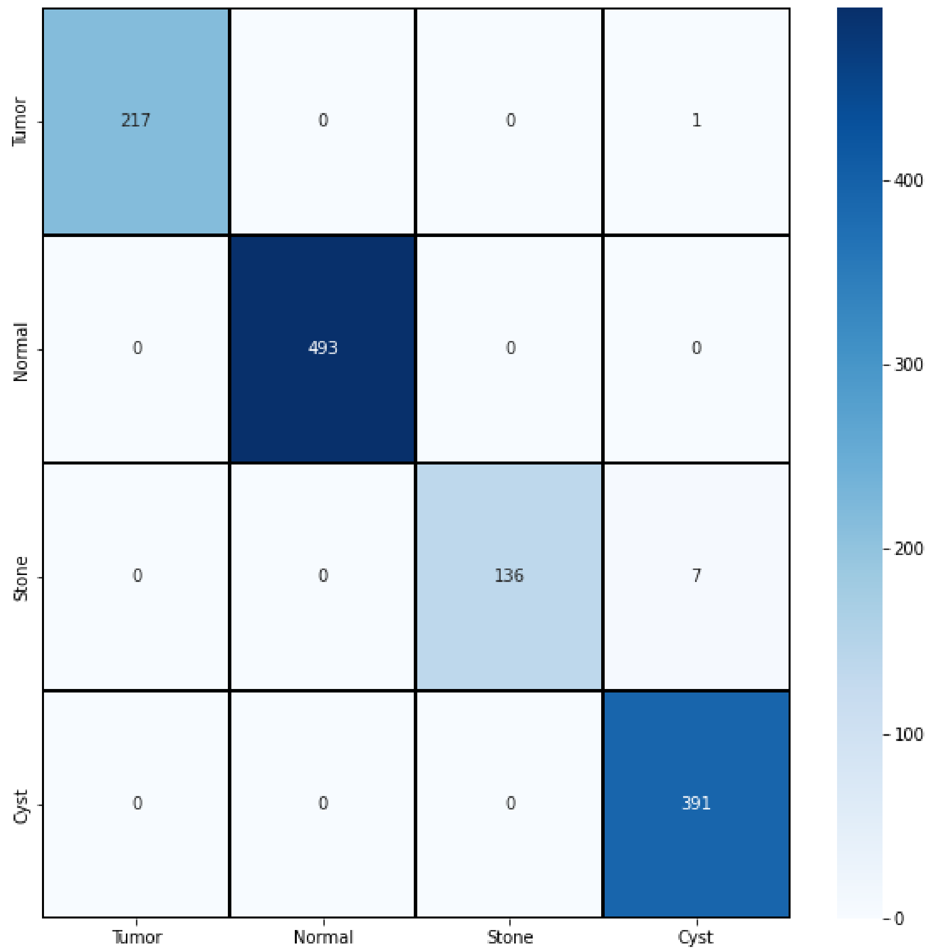

Figure 19: VGG16

(iii) ResNet34

In this figure we see that there is a two portion of confusion metrics. One is train confusion metrics and another is validation confusion metrics. In train confusion metrics we observed that 2102 cysts, 2160 normal, 540 stone and 374 tumor have been detected. In validation confusion metrics we observed that 1303 cysts, 1124 normal, 172 stone and 0 tumor have been detected.

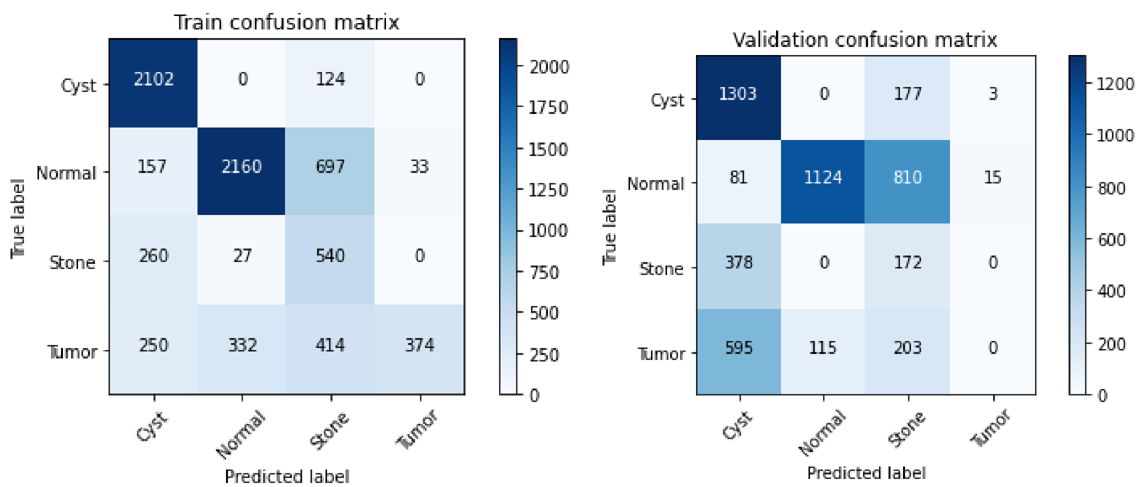

Figure 20: ResNet34

(iv) DenseNet201

After applying the DenseNet201 algorithm on the dataset we find that there are 391 cysts detected, 439 normal or healthy kidney detected, 130 stone detected and 231 tumor detected.

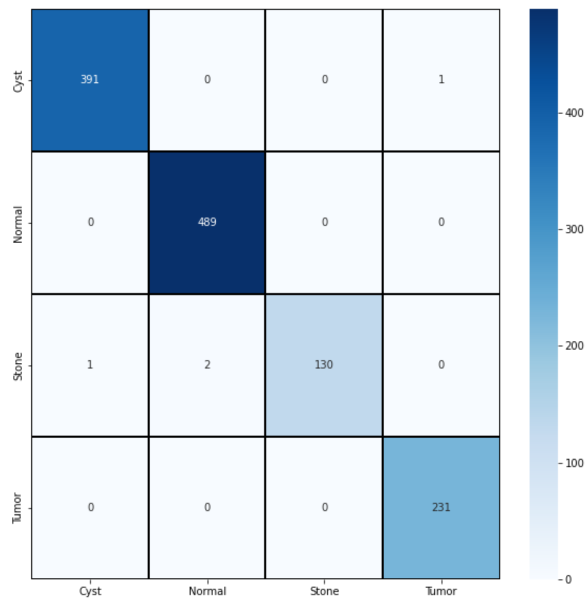

Figure 21: DenseNet201

(v) EfficientNetB1

After applying the EfficientNetB1 algorithm on the dataset we find that there are 1248 cysts detected, 1726 normal or healthy kidney detected, 329 stone detected and 449 tumor detected.

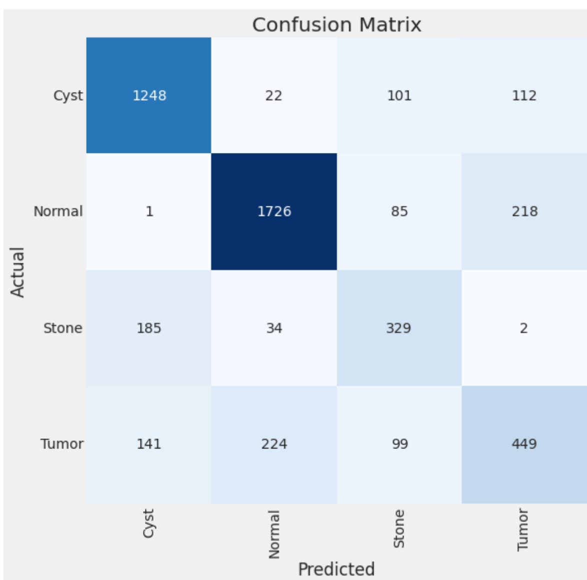

Figure 22: EfficientNetB1

4.4 Comparative Analysis

A portion of the information I worked with has been used by other researcher. After applying the facts and algorithms, they used machine learning. My model and those are contrasted in the table below. For the order of illnesses such Stones and Cysts, a few ML techniques were applied, including ANN, SVM, Naive Bayes, and Random Forests. SVM outperformed ANN and Naive Bayes, which had accuracy of about 72% and 80% respectively, in the comparison. This study achieved an average exactness of 80%. A precision of 75% was obtained using the CNN model, which is insufficient for various forms of renal illness.

Table III: Comparative Analysis

Problem Domain	**Images used**	**Classifier**	**Accuracy**	**References**
Detection	7563	SVM, Naïve Bayes	80%	[14]
Detection	276	ANN	72%	[18]
Detection	9700	CNN	74%	[15]
Detection	12446	**VGG16**	**99%**	**Proposed Model**

4.5 Limitation of Work

(i) Dataset could be more larger.

(ii) I could have used more algorithms, couldn’t used due to shortage of time.

(iii) It takes huge time to do thorough researches. Since I had to submit my work within a very short span I may have left many lacking doing my research properly.

CHAPTER 5
Conclusion and Future Work

5.1 Conclusion

In order to aid professionals in medical diagnosis, we proposed in this study an intelligent using deep-learning system for the automatic finding of computed tomography images. The goal is to automatically identify and categorize each object in the image. To prevent the overfitting issue while lowering the training time and assisting the model's improved generalization, various regularization, transfer learning, and data augmentation strategies were used. One of the most promising deep learning techniques for real-world image classification applications is transfer learning. In this study, transfer learning is utilized to categorize images of kidneys using a variety of pre-trained models. In this article, five (CNN, VGG16, Resnet34, DenseNet201, EfficientNetB1) potent pretrained models with two optimization techniques are compared. On the kidney dataset, all five models had good classification accuracy, but the VGG16 model beat the others and it gave us 99% accuracy.

5.2 Future Work

In this paper, we basically discussed about how to detect kidney disease by applying deep learning algorithms. In future we will extend our work as a software based work. Our target is to make a software that can easily detecting any kind of disease easily. We also want to apply our work in different medical fields to detecting disease very easily.

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Kidney disease detection

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