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# A Survey of Kidney Cancer Analysis Using Machine Learning and Deep Learning Algorithms



**Abstract:** - A recent and emerging public health concern is kidney disease, particularly Chronic Kidney Disease (CKD), characterized by a gradual decline in kidney function due to various ailments. Kidney cancer, a potentially fatal form of cancer, requires accurate staging for effective treatment selection, with Stage 1 being a crucial point for decisions. Physicians often face challenges in accurately determining cancer stages, leading to potential under- or over-treatment. Kidneys play a vital role in filtering blood, removing waste and excess fluids, excreted as urine. Advanced renal disease can cause dangerous build-ups of fluids, electrolytes, and waste. In early stages, kidney disease may exhibit minimal symptoms, often progressing unnoticed until more advanced stages. Kidney cancer arises when kidney cells undergo abnormal growth and lose control. Treatments for kidney cancer encompass a range of options, including surgical procedures, chemotherapy, and radiation therapy. Early detection remains pivotal for effective intervention, echoing the universal importance seen in managing all types of cancer. In contrast, managing chronic kidney disease focuses on minimizing kidney damage by targeting its root causes, although addressing these factors may not always halt the disease's progression. In advanced stages, kidney cancer can potentially lead to kidney failure, a life-threatening condition necessitating artificial filtration methods like hemodialysis or surgical interventions for survival. “Various risk factors encompassing dietary habits, environmental exposures, and living conditions contribute significantly to sudden and often unnoticed illnesses among many individuals. Physicians commonly encounter challenges in accurately determining the stages of cancer, potentially leading to either under treatment or overtreatment. The diagnosis process for chronic renal disease is often fraught with risks, high costs, time-intensive procedures, and invasiveness. Consequently, numerous illnesses remain untreated until they reach advanced stages, especially prevalent in regions with limited resources, highlighting disparities in healthcare accessibility and early detection. Early detection is vital for doctors to save lives.

Detecting kidney conditions early can help prevent kidney damage and slow down Kidney Cancer progression. “Researchers are exploring various methods to identify kidney disease at an early stage. This research aims to understand and improve early prediction techniques for this condition. To categorize Kidney cancer, researchers use different classification strategies like Artificial Neural Networks (ANN), Naive Bayes, Support Vector Machines (SVM), Adaptive Deep Convolutional Neural Network (AHDCNN), Alex Net, U-Net 2D, ada boost classifiers, and Linear Discriminant methods.

**Keywords:** Kidney Cancer, Classification, Prediction, ANN, RCGNET, CNN.

## 1. Introduction

In 2023, an estimated 81,800 adults (52,360 men and 29,440 women) in the United States will be diagnosed with kidney cancer. Worldwide, an estimated 431,288 people were diagnosed with kidney cancer in 2020. In the United States, kidney cancer is the sixth most common cancer for men. It is the ninth most common cancer for women. The average age at diagnosis for people with kidney cancer is 64, and most people are diagnosed between the ages of 65 and 74. Kidney cancer is not common in people younger than age 45. Men are twice as likely as women to develop the disease. It's also more common in Native American and Black populations. Kidney cancer is much less common in children. However, 500 to 600 children are diagnosed with a Wilms tumor (a type of kidney cancer) every year in the United States. The kidneys filter blood to remove impurities, excess minerals and salts, and extra water. Every day, the kidneys filter about 200 quarts of blood to generate 2 quarts of urine. The kidneys also produce hormones that help control blood pressure, red blood cell production, and other bodily functions.

Kidney cancer is characterized by abnormal cell growth in kidney tissue, forming tumors over time. When these tumors become cancerous, they can spread to other tissues and organs, a process known as metastasis. There are several types of kidney cancer, including renal cell carcinoma (RCC), which is the most prevalent in adults, transitional cell cancer originating in the renal pelvis or ureters, and renal sarcoma, the rarest form originating in the kidney's connective tissues.

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Wilms' tumor is the predominant kidney cancer found in children, constituting approximately 5% of kidney cancer cases. Symptoms of kidney cancer include blood in urine, a lump or mass in the kidney area, flank pain, vomiting, fatigue, loss of appetite, weight loss, low-grade fever, bone pain, high blood pressure, anemia, dry, itchy skin, difficult-to-control hypertension, and swelling of the feet and ankles.

Global healthcare systems are expected to undergo a significant transformation as a result of digital technologies in modern healthcare. Smart healthcare quickly navigates health data, responds to medical environment requirements, and connects people, services, and institutions via digital technology [1]. The potential of smart healthcare to connect the numerous actors in medical systems benefits a variety of parties, including patients, doctors, hospitals, and insurance companies. This is made possible by new and developing technologies like artificial intelligence (AI), the Internet of Things (IoT), fog computing, cloud services, blockchain, monitoring devices, 5G technology, and the Internet of Medical Things (IoMT) [5]. Wearable sensors are referred to as the IoMT when they interact with other clinical systems and medical apparatus to support medical-related tasks. The IoMT combines medical equipment with IoT technologies. IoMTs are the future of healthcare systems because they connect every medical device to the Internet and are constantly monitored by medical professionals [6]. Although Routing Protocol for Low Power and Lossy Network (LLN) is intended for networks with static topologies, IoT application domains place a high priority on mobility.

IoMT is a brand-new IoT concept that consists of mobile devices. Mobility detection ought to be supported by an IoMT routing protocol. Due to the absence of a mobility detection mechanism in RPL, mobile topologies are faced with a number of difficulties. For instance, disconnection, which occurs when a mobile node leaves the range of its preferred parent, results in packet delivery rates that are low, data loss, and transmission delays. Due to the mobile node's resource constraints, designing an effective routing protocol for IoT is essential for maintaining its energy [4].

Unfortunately, it is difficult to identify kidney cancer early on using standard clinical methods, making it one of the deadliest [21]. Even though renal carcinoma is one of the ten most lethal malignancies, there is currently an absence of study in this field. There are many different varieties of cancer, which has dominated medical research and slowed the development of cutting-edge approaches for detection and therapy. Life expectancy is typically estimated to be less than one year for patients with kidney cancer, who have limited treatment choices for decades. A clinician will consequently be able to identify the condition swiftly and readily with the aid of automatic diagnostic technologies, improving patient survival. It is challenging to recognize early kidney disease despite the widespread usage of classification systems in many automatic medical diagnostic instruments. Applying the tool and Chronic Renal Disease (CKD) impact on kidney function and structure can lessen the testing burden. Complications from a longer illness may include weak bones, high Blood Pressure (BP), anemia, nerve damage, problems with the blood vessels in the heart, etc. Depending on the Glomerular Filtration Rate (GFR) stage, the disease manifests at various levels [22] [1]. Early detection and treatment of kidney cancer increase the likelihood of a successful recovery for the patient. Kidney segmentation is therefore a crucial step in computer-assisted urology diagnosis and therapy and a requirement for surgical planning [8]. Accurate segmentation offers structural data on kidney shape anomalies and measures of kidney size, which physicians can utilize to examine major clinical problems like cancer [9] [3].

The use of statistical investigation to learn from ecological data is one of the more well-liked recent developments in machine learning approaches. This increases the intelligence of the network applications and prevents them from following a set of static rules that have been preset [23]. The machine learning technique improves performance for response times, network resource management, and security threats while also streamlining decision-making [7].

Image processing Medical Technique. Image processing is widely used across various industries like robotics, biometrics, security, surveillance, remote sensing, and medical imaging. The effectiveness of image processing tasks greatly depends on the quality of the test image. Medical imaging techniques, including ultrasound sonography (US), computed tomography (CT), and magnetic resonance imaging (MRI), play a crucial role in diagnosing illnesses. However, the uniformity of medical images poses challenges in identifying regions of interest and patterns, blurring the boundaries between organs and surrounding areas. Radiologists often prefer

CT imaging due to its ability to produce high-resolution images with clear anatomical features, excellent contrast, and exceptional spatial resolution.

The diagnosis and assessment of renal tumors frequently utilize multiphase abdominal computed tomography (CT). On the basis of the tumors enhancing properties, multiphase CT is often analyzed. Nevertheless, there are significant image-level feature overlaps amongst renal tumor subtypes, which complicate subtype categorization and lead to inter-observer variation. The need for developing automatic solutions that can lower misdiagnosis and interobserver variability is highlighted by these clinical issues. On a number of medical image analysis tasks, Deep Learning (DL) based on Convolutional Neural Networks (CNNs) has recently demonstrated promising outcomes. Tumor segmentation and classification for renal lesions have been done using deep learning. Nevertheless, lesions were typically only divided into the two classes (benign/malignant) or the three Renal cell carcinoma (RCC) classes in earlier studies on tumor classification [24]. Furthermore, the previous diagnosis techniques needed radiologists to manually draw the locations of tumors in order to identify lesions [9]. Complex and effective methods for pattern recognition include deep learning neural networks. In identifying items in nature scenes, such as various breeds of cats, dogs, mountains, etc., they demonstrated a high level of accuracy. When it came to classifying natural scene items, the DLNNs emerged victorious in significant international competitions [10].

The remaining sections of this work are structured as follows. An overview of the relevant studies is presented in Section 2. The various machine learning approaches are discussed in Section 3. In section 4, we present the feature selection methods, and section 5 presents the discussion and conclusion.

## 2. Literature Survey

A comprehensive investigation has been conducted to explore the methods utilized in the early detection and prevention of kidney Cancer. Following are the research papers reviewed:

Alzu'bi, D., Abdullah, M., Hmeidi, I., AlAzab, R., Gharaibeh, M., El-Heis, M., Almotairi, K.H., Forestiero, A., Hussein, A.M. and Abualigah, L., present "Kidney tumor detection and classification based on deep learning approaches: a new dataset in CT scans This study employs four methods, including VGG16, ResNet50, and two modified 2D-CNN models, to assess kidney tumor injury and identify tumor types based on renal CT scans.

The features extracted from the CT scans aid in distinguishing between normal and tumor, as well as benign and malignant cases, through training and testing methods. The proposed 2D-CNN models exhibit effectiveness, with accuracy rates of 60%, 96%, and 97% for VGG16, ResNet50, and 2D-CNN detection models, respectively. The classification 2D-CNN model achieves a 92% accuracy rate in distinguishing between tumor and non-tumor cases.

Despite these achievements, the study has a limitation as it does not perform classification tasks for specific tumor subtypes.

This study describe The RCCGNet is designed with a shared channel residual (SCR) block, enabling the network to understand feature maps related to various input versions through two parallel paths. In this configuration, the SCR block facilitates information sharing between different layers, ensuring that shared data is processed independently to offer mutually beneficial enhancements. This study describe a fully automated deep learning framework called a Renal Cell Carcinoma Grading Network (RCCGNet) for the detection of malignancy levels of renal cell carcinoma (RCC) in kidney histopathology images. This paper is the first to propose an end-to-end automatic grading of kidney cancer from kidney histopathology images. Te performance of the proposed RCCGNet was evaluated by the most preferred quality metrics and achieved 90.14% of accuracy, and 89.06% F1-score on the proposed KMC kidney dataset, and on the Break His dataset, the proposed RCCGNet achieved 90.09% of accuracy, and 88.90% F1-score. Limitation of this research is It did not focus on the considerable extension of the kidney dataset and other pathological dataset.

da Cruz, L.B., Araujo, J.D.L., Ferreira, J.L., Diniz, J.O.B., Silva, A.C., de Almeida, J.D.S., de Paiva, A.C. and Gattass, M., present "Kidney segmentation from computed tomography images using deep neural

network", *Computers in Biology and Medicine* This study introduces an automated approach for kidney delineation in computed tomography (CT) images, employing image processing methods and deep convolutional neural networks (CNNs) to mitigate false positives. The primary methodology comprises four key steps: (1) obtaining the KiTS19 dataset, (2) narrowing the scope with AlexNet, (3) initial segmentation via U-Net 2D, and (4) false positive reduction through image processing techniques aimed at preserving the largest kidney elements. In this method it demonstrates Efficient resolution of kidney segmentation in CT scans is achieved by employing deep neural networks. Deep neural networks play a key role in defining the problem scope and achieving precise segmentation of kidneys. The application of image processing techniques in this approach effectively minimizes false positives during kidney segmentation. Due to the huge number of parameters that were empirically calculated in the two CNN models, it was unable to take into account alternate parameter optimization strategies.

Ma, F., Sun, T., Liu, L. and Jing, H., present "Detection and diagnosis of chronic kidney disease using deep learning-based heterogeneous modified artificial neural network", In this study, a method called Heterogeneous Modified Artificial Neural Network (HMANN) is presented, employing deep learning for the detection of chronic renal disease. The process of image segmentation in chronic renal disease detection is prone to noise and complexity, prompting the need for an algorithm capable of handling missing and noisy values while providing classification This paper employed feature reduction based on the study's significant findings to trim redundant features and highlight key predictive attributes for Chronic Kidney Disease (CKD). Furthermore, novel factors were uncovered, enhancing classifiers' precision in CKD detection compared to current methods, achieving an impressive 97.5% accuracy. Nonetheless, it is important to acknowledge that this technique exhibited occasional instances of suboptimal performance.

Hsiao, Chiu-Han, Ping-Cherng Lin, Li-An Chung, Frank Yeong-Sung Lin, Feng-Jung Yang, Shao-Yu Yang, Chih-Horng Wu, Yennun Huang, and Tzu-Lung Sun. present "A deep learning-based precision and automatic kidney segmentation system using efficient feature pyramid networks in computed tomography images" This study describes new method for kidney segmentation in CT images of abdomen with the workflow of hyper parameter optimizations. First, encoder decoder architecture was adopted to combine EfficientNet-B5 and FPN for kidney segmentation. Secondly, a series of experiments were undertaken to fine-tune the model performance through exploration of various windowing methods, loss functions, and data augmentation techniques. Subsequently, the model underwent rigorous testing on both the KiTS19 and 3DIRCADb-01 datasets for kidney segmentation. The experimental findings indicate that optimal performance is achieved with specific configuration parameters, including a window range of -79 to 304 HUs, utilization of the BCE loss function, and employing non-augmented data. The problems of data distribution imbalance were not tackled. Dice score=91.5%, Recall=96.43%, Precision=87.22%, Intersection over Union (IoU) score=84.42%

Abdelrahman, A. and Viriri, S., present "FPN-SE-ResNet Model for Accurate Diagnosis of Kidney Tumors Using CT Images, this study describes using a SE-ResNet FPN model, this paper presents a methodology for segmenting tumors and kidneys in CT slices. The method involves three main phases: data preparation, segmentation, and an ensemble phase. Preprocessing steps such as data preparation, down sampling, and resizing are crucial for classifying CT images. Evaluation metrics like Intersection over Union (IoU) and F1-score are discussed as standard measures for assessing image segmentation tasks. The study explores the effectiveness of the Feature Pyramid Network (FPN) architecture in conjunction with various models from the SE-ResNet family for segmenting kidney cancer CT images. The complexity had led to longer training periods.

McGough, W., Buddenkotte, T., Ursprung, S., Gao, Z., Stewart, G. and Crispin-Ortuzar, M., present "Automated Small Kidney Cancer Detection in Non-Contrast Computed Tomography", This study describe automated RC classification pipeline optimized for NCCT and provide evidence of its efficacy in detecting small RCs. Our 2D tile model (AUC 0.804) far exceeds previous attempts at detecting small RCs automatically in NCCT (AUC 0.562), and may enable RC screening via NCCT. In training, this method avoided the cancer/non-cancer dichotomization due to cysts in the training data. Specificity=92.7%, sensitivity=61.9%. This paper present automated Radiological Contour (RC) classification pipeline specifically optimized for Non-Contrast Computed Tomography (NCCT). Our 2D tile model demonstrates a

remarkable efficacy in detecting small RCs, with an Area Under the Curve (AUC) of 0.804. This surpasses previous attempts at automatic small RC detection in NCCT, where the AUC was only 0.562. The superior performance of our pipeline suggests its potential to facilitate RC screening via NCCT, presenting a significant advancement in the field of automated radiological analysis.

Majid, M., Gulzar, Y., Ayoub, S., Khan, F., Reegu, F.A., Mir, M.S., Jaziri, W. and Soomro, A.B., present "Enhanced Transfer Learning Strategies for Effective Kidney Tumor Classification with CT Imaging" In this study, we present a hybrid approach that combines the Light Gradient Boosting Method with Grey Level Co-occurrence Matrix (GLCM) computation for the automatic classification of kidney tumors from CT kidney image datasets. To enhance the training process, various preprocessing techniques and image resizing methods were employed to reduce model complexity and accelerate training. Leveraging Light GBM, renowned for its speed, efficiency, and high predictive accuracy among machine learning models, proved to be effective in this context. Furthermore, we introduced two fine-tuned Transfer Learning (TL) models, namely ResNet-101 and DenseNet-121, within this framework for kidney tumor prediction. The performance of these models was comprehensively assessed using diverse performance metrics and compared against state-of-the-art methods. Our findings highlight the superiority of the fine-tuned TL models, with DenseNet-121 achieving an impressive accuracy of 98.22%.

Limitation is It potentially missed out valuable insights and alternative solutions. Accuracy= 94.09%, precision=95.10%, recall=93.5%, and F1-score=93.95%.

Uhm, K.H., Jung, S.W., Choi, M.H., Shin, H.K., Yoo, J.I., Oh, S.W., Kim, J.Y., Kim, H.G., Lee, Y.J., Youn, S.Y. and Hong, S.H., present "Deep learning for end-to-end kidney cancer diagnosis on Page 17 multi-phase abdominal computed tomography", This study shows that an end-to-end deep learning model can match radiologist-level performance in diagnosing kidney cancer using CT data. The proposed model excelled in fine-grained classification, distinguishing between five major pathological subtypes, including benign and malignant tumors. These findings underscore the potential of fully automated systems to aid radiologists in diagnosing kidney cancer patients. Larger studies are required to validate the model's applicability in clinical practice. Recently, many deep learning-based semantic segmentation methods have been developed, such as FCN32, U-Net33, Deeplab V3+34, and PSPNet35. According to the kidney tumor segmentation challenge (KiTS19) reports36, the 3D U-Net architecture37 achieved the top performance over other methods. This paper employed a 3D U-Net for kidney and tumor segmentation, categorizing each voxel in a CT volume into three classes: background, kidney, and tumor. Training involved 848 CT scans, encompassing four contrast phases, with volumes resampled to a  $1.5 \times 1.5 \times 3 \text{ mm}^3$  voxel size. Network parameters underwent optimization using stochastic gradient descent on the combined cross-entropy and Dice loss function. Hyperparameters, including batch size and learning rate, were selected following the guidelines of nnU-Net21. This component effectively generates segmentation masks for the kidney and tumor in each phase of the CT volume.

The Deep Learning Neural Networks are complex powerful methods for pattern recognition. They proved very accurate in distinguishing natural scene objects such as different types of cats, dogs, mountains, etc. The DLNNs were ultimate winners in large international competitions for natural scene objects classification [10]. In [10] paper The aim of this research is to develop a system utilizing deep learning neural networks (DLNNs) for precise kidney cancer stage assessment. The proposed system operates on cropped computer tomography images featuring kidney cancer, with a specific focus on the DLNN's capability to differentiate between kidney cancer at Stage 1 and higher stages.

he semantic comprehension of image cannot be separated from the segmentation technology. The image is essentially the two-dimensional matrix formed by a series of pixel while semantic segmentation actually focuses on grouping these pixels in image according to the different expression meanings in the image It is usually called as segmentation. [11] Deep learning, particularly convolutional neural networks (CNNs), has surpassed the state-of-the-art in various image recognition and target detection tasks within computer vision. Additionally, CNNs exhibit exceptional performance in the semantic segmentation of natural images, marking a significant advancement as deep learning integrates into the realm of computer vision. Leveraging

convolutional neural networks (CNNs) in training methodologies can notably enhance the accuracy of semantic segmentation. This study introduces a metric learning approach that constructs a deep convolutional neural network structure utilizing SCNN and ResNet networks to extract image features and mitigate the influence of interfering factors on these features.

In Woo, S., Kim, D., Cho, D. and Kweon, I.S [13] aimed to focus on scene graph generation, aiming to construct a visually-grounded scene graph for a given image. In the scene graph, objects are nodes, and their relationships are depicted as directed edges. Each node is defined by an object bounding box with a category label, while each edge is marked by a predicate label, connecting two nodes in the form of a subject-predicate-object triplet. The performance is enhanced in this work by introducing a global context encoding module and a geometric layout encoding module, resulting in the construction of a LinkNet.

In paper [14] introduces a novel feature descriptor named SLIF to address the challenge of image matching. The approach utilizes a distinctive sampling pattern inspired by the structure of an orb web. This pattern selectively captures pictorial information from the neighborhood of each detected feature point, which is then encoded into a precise and distinctive feature descriptor.

In paper [15] introduces a new local pattern descriptor named Local Vector Pattern (LVP). The study explores and evaluates LVP as a method for creating a robust and efficient representation for various applications. The paper introduces a unique vector representation method by computing diverse directions at various distances, effectively capturing 1D direction and structural details of facial texture. Leveraging this vector representation, the Local Vector Pattern (LVP) encodes multiple pairwise directions as a facial descriptor, enhancing the characterization of micro pattern structures.

Kabir, H.D., Abdar, M., Khosravi, A., Jalali, S.M.J., Atiya, A.F., Nahavandi, S. and Srinivasan [16] introduces a novel Deep Neural Network (DNN) model named SpinalNet, inspired by the chordate nervous system's unique approach to connecting sensing information and making local decisions. SpinalNet addresses the computational intensity of large input data in traditional feed-forward NN models by gradually processing inputs and making local decisions akin to the spinal cord's function. The effectiveness of SpinalNet is demonstrated on various benchmark datasets, showcasing improved classification accuracy and regression error. Additionally, SpinalNet proves to be less computation-intensive than its counterparts. When combined with VGG-5, SpinalNet achieves state-of-the-art performance in handwritten character recognition datasets, and with transferred initialization, it excels in color image datasets. The paper encourages researchers to further enhance SpinalNet's accuracy and apply it to diverse real-world scenarios.

Yao, R., Wang, N., Liu, Z., Chen, P. and Sheng, X [17] presented convolutional neural network (CNN) and long short-term memory (LSTM) this two method are used for the detection of intrusions in AMI. This paper introduces a novel intrusion detection model, integrating CNN and LSTM through cross-layer feature fusion. The proposed model demonstrates enhanced effectiveness in identifying intrusion information within Ambient Intelligence (AMI) when compared to other models. CNN-LSTM intrusion detection model exhibits better performance than traditional intrusion detection models.

Chen, G., Ding, C., Li, Y., Hu, X., Li, X., Ren, L., Ding, X., Tian, P. and Xue, W [20] introduces the Adaptive Hybridized Deep Convolutional Neural Network (AHDCNN) for the early prediction and diagnosis of Chronic Kidney Disease (CKD). The system employs deep learning to identify distinct subtypes of lesions from CT images in renal cancer. After initial data analysis and handling missing values, relevant features associated with kidney disease are extracted and input into a classifier to identify variations in kidney patterns. The system undergoes training in each hidden layer to recognize irregular patterns using a deep-belief network. The study explores the efficient use of learning and activation mechanisms to effectively avoid kidney disease, considering regression and distribution of the data.

Lin, J., Knight, E.L., Hogan, M.L. and Singh, A.K [21] presented Comparison of Prediction Equations for Estimating Glomerular Filtration Rate in Adults without Kidney Disease The MDRD equations, however, consistently underestimate GFR, whereas the CG equations consistently overestimate measured GFR in people with normal renal function.

Monica A. Fisher\* and George W. Taylor [22] provided the probability of chronic kidney disease can be estimated using the b coefficients from the most parsimonious final model, considering 12 recognized and suspected risk factors. Subgroups were identified ranging from virtually no probability (0.06%) to very high probability (98%). Individual risk can be estimated as the probability that individuals with the same 12 specific characteristics have chronic kidney disease, utilizing the formula provided in the Statistical Analyses section.

Fatima Hussain, Rasheed Hussain, Syed Ali Hassan, and Ekram Hossain [23] presented review of Machine Learning in IoT Security Current Solutions and Future Challenges

Seokmin Han & Sung Il Hwang & Hak Jong Lee [24] introduce In this paper, we utilize an image-based deep learning framework to differentiate between the three primary subtypes of renal cell carcinoma (clear cell, papillary, and chromophobe) utilizing computed tomography (CT) images. Our approach employs a deep learning neural network, which is trained to classify the subtypes of renal cell carcinoma. This involves using the manually drawn Regions of Interest (ROIs) from the CT images as inputs and the corresponding biopsy results as labels for training the neural network.

Hafiane, A., Seetharaman, G. and Zavidovique, B [25] presented Local Binary Pattern which used for Textures Classification and Median based binary pattern used Statistical Characterization. This paper describes a method for characterizing textures based on local patterns. The texture attributes are represented as a distribution of these patterns, and a multi-dimensional histogram serves as a cue for analysis. The use of median-based binary patterns is highlighted for its excellent discriminative properties, leading to high performance in texture classification. This paper also addresses various factors influencing the detection and recognition of textures. These factors include illumination, resolution, and rotation. Specifically, rotations are identified as more challenging for the proposed method, indicating potential limitations in handling rotated textures.

Khalid Haseeb 1, Irshad Ahmad 1, Israr Iqbal Awan 1, Jaime Lloret 2,3 and Ignacio Bosch 4[26] present SDN-Enabled Model. The system is structured into three primary layers: the sensing network, SDN architecture, and user applications. The sensing layer encompasses sensors, actuators, and communication devices, which collaborate to gather patients' data and facilitate seamless interaction for efficient transmission within the system.

Muhammad Umar Nasir 1 , Muhammad Zubair 2 , Taher M. Ghazal 3[27] introduce the proposed model used the Internet of Medical Things (IoMT)-based transfer learning technique with different deep learning algorithms to predict kidney cancer in its early stages

### 3. Deep Learning And Machine Learning Algorithms

#### Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) have become a popular and powerful tool in image processing due to their ability to automatically learn hierarchical features from input data. CNNs are commonly used in image processing: Image Classification, Object Detection, Semantic Segmentation, Image Generation, Feature Extraction, Medical Image Analysis. A Convolutional Neural Network (CNN) is a neural network architecture that operates on the principle of weight sharing. Some key aspects of CNNs are Convolutional Layers in Which Convolution involves sliding a small window (kernel/filter) over the input image and applying element-wise multiplication to extract local patterns or features. This allows the network to automatically learn spatial hierarchies of features. Pooling layers are often used to down sample the spatial dimensions of the input volume, Activation functions, such as ReLU (Rectified Linear Unit), are applied after convolutional and fully connected layers to introduce non-linearity into the network, allowing it to learn more complex relationships in the data. It's important to note that the success of CNNs in image processing is often attributed to their ability to automatically learn and extract hierarchical features, reducing the need for manual feature engineering. The field of CNNs in image processing is dynamic, and researchers continually explore new architectures and techniques for improved performance

### **Artificial Neural Network (ANN)**

The mathematician and neurophysiologist Warren McCulloch and Walter Pitts created a model of a neuron in the 1940s. The switch-like model has two inputs and a single binary output. The neuron gets input from other neurons, and depending on the overall weighted input, it either produces a zero or a one, or is active or inactive [32]. In paper [4], a deep learning-based Heterogeneous Modified Artificial Neural Network (HMANN) method has been proposed for the early detection, segmentation, and diagnosis of chronic renal disease. An Artificial Neural Network (ANN) is a computational model inspired by the human brain. It consists of interconnected nodes called neurons, organized in layers. Information is processed through these layers, and the network learns by adjusting weights associated with connections between neurons. ANNs are used for tasks like pattern recognition, classification, and regression. Training involves feeding data through the network, calculating errors, and adjusting weights to improve performance. Common types include Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Generative Adversarial Networks (GAN). ANNs are a key technology in machine learning and have diverse applications.

### **Support Vector Machine (SVM)**

In the late 1990s, Vapnik, Cortes, and Boser were the pioneers who presented the concept of a classifier that was drawn from statistical learning theory [31]. This classifier is known as Support Vector Machine (SVM), and it achieved considerable attention in the field of machine learning in that same year. A Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks. Its primary objective is to find a hyperplane that best separates data points of different classes in a high-dimensional space. The "support vectors" are the data points closest to the decision boundary (hyperplane). SVM aims to maximize the margin, the distance between the support vectors and the decision boundary, making the model robust to new data. It is effective for both linear and non-linear data, thanks to kernel functions that transform the input space. SVM is widely used for image classification, text classification, and other pattern recognition tasks.

### **Link Net model**

LinkNet is a deep learning architecture designed for semantic image segmentation. Semantic segmentation is the task of classifying each pixel in an image into a predefined class or category, effectively labeling every pixel with its corresponding object or region. LinkNet was introduced to improve the accuracy and efficiency of semantic segmentation models. LinkNet is an effective and efficient architecture for semantic image segmentation, with a particular emphasis on preserving fine details and object boundaries. It achieves this through the use of skip connections and link modules, making it a valuable tool for a variety of computer vision applications.

### **Alex Net**

It is CNN Based Model used for image processing techniques, such as normalization and histogram specification. AlexNet demonstrated the effectiveness of deep learning in image classification tasks and set the stage for the development of more sophisticated architectures. Its success paved the way for the deep learning revolution in various domains beyond computer vision. It was developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, and won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012.

### **U-Net**

U-Net is a fully convolutional Artificial Neural Network (RNA) proposed for the segmentation of biomedical images [41], that since 2015 has been surpassing existing methods in several biomedical image segmentation challenges. This network is a specific type of deep and forward network whose architecture. This distance-based algorithm is most effective when dealing with continuous attribute values, although it can be adapted to accommodate categorical attributes as well. It operates by approximating the classification of an unknown instance by identifying and classifying the most similar instances from the training set [42]. This approach is



akin to classifying the k-nearest neighbors, prioritizing the classification of the nearest neighbor, even when multiple cases exist within the training set.

### SpinalNet

This method proposed in paper [16] The SpinalNet architecture aims to achieve enhanced accuracy while requiring fewer computations. Unlike traditional neural networks (NNs), where hidden layers sequentially receive inputs from the previous layer, apply activation functions, and pass outputs to the next layer, SpinalNet introduces a novel structure. In SpinalNet, each layer is divided into three splits: input split, intermediate split, and output split. The input split of each layer receives a portion of the inputs, while the intermediate split receives outputs from the intermediate split of the previous layer and outputs from the input split of the current layer. This division significantly reduces the number of incoming weights compared to traditional deep neural networks (DNNs). SpinalNet can serve as a fully connected or classification layer in DNNs and supports both traditional learning and transfer learning. Experimental results demonstrate notable error reductions with lower computational costs across various DNN architectures.

### Conclusion

This study's objective was to examine and evaluate the outcomes of utilizing these algorithms in the field of medicine to anticipate disease. When used properly and in conjunction with tools and approaches that can improve its efficacy in identifying the disease, machine learning unquestionably produces positive results. It is possible to forecast kidney disease using different classifications. The algorithmic classifier can also be used to predict the severity of chronic renal disease. Although there are several parameters in this study, KD is constrained. However, unless each discovery of a correlation between the other research in the relevant component previous knowledge KD was confirmed, some new results were produced. In the future, the algorithm can be enhanced to integrate symptoms as additional input, leveraging historical patient data to predict the disease more accurately. Moreover, exploring various feature selection techniques holds promise for further refining the categorization outcomes, potentially enhancing the algorithm's performance even further.

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