AI-KIDNEY DISEASE DETECTION

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***Abstract*—This research seeks to create and test a new AI model that combines YOLO, Seg-Net, VGG-16, VGG-19, and Efficient-Net to improve the accuracy and efficiency of kidney disease diagnosis based on medical imaging. The model streamlines the detection, segmentation, and classification of kidney disorders to minimize diagnostic time and enhance clinical outcomes. It also compares the performance of different models to determine the most effective way for diagnosing renal disease. A publicly available medical image dataset of 500 kidney images was employed, balanced across training and testing sets. The architecture combined YOLO for object detection, Seg-Net for segmentation, and VGG16, VGG-19, and Efficient-Net for feature extraction and classification. Robustness was guaranteed by a 5-fold cross-validation with a 95% confidence interval. Statistical power was established as 0.8 via G-power, alpha = 0.05, and beta = 0.2. Performance parameters like accuracy, sensitivity, specificity, and computational expense were tested. The architecture showed better performance, with YOLO reporting 97.2% accuracy in detection and Efficient-Net performing better than other classifiers (98.1% accuracy). Significant differences between models were observed with a p-value of 0.003 (p ¡ 0.05), indicating the efficacy of the integrated method. The computational efficiency increased by 40% from conventional procedures. The combination of YOLO, Seg-Net, VGG-16, VGG-19, and Efficient-Net highly improves kidney disease diagnosis accuracy and efficiency. The automated nature of medical imaging analysis by the framework makes it an invaluable application in clinical environments. Future work may investigate hybrid models and larger datasets to further enhance performance.**

***Keywords* — Diagnosis of kidney disease, medical imaging, YOLO, Seg-Net, VGG-16, VGG-19, Efficient-Net, deep learning, image segmentation, AI in healthcare.**

I. INTRODUCTION

The global kidney disease burden needs novel approaches to fast and precise diagnosis. Traditional diagnostic procedures, which rely on manual interpretation of medical pictures, are time-consuming, prone to human error, and lead to delayed or ineffective therapies. These shortcomings highlight the gap in healthcare infrastructure, where efficacy and accuracy are compromised. Advances in artificial intelligence (AI) and deep learning provide[1] a transformative potential to address these demands. Through the automation of kidney abnormality detection, segmentation, and classification, AI has the potential to improve diagnostic accuracy, decrease processing time, and lighten the workload on healthcare personnel. This project brings together such state-of-the-art models as YOLO, Seg-Net, VGG-16, VGG19, and Efficient-Net into a single framework, intending to transform kidney disease diagnosis. The motivation is to enhance patient outcomes through early and precise diagnosis, lower healthcare expenditures, and save lives. Closing the gap between technology and healthcare, this framework promises to establish a new benchmark in medical imaging, offers the potential to drive further innovation in AI-based healthcare solutions.

Diagnosis of kidney diseases is mostly dependent on image analysis by physicians, which is time-consuming, susceptible to error, and frequently results in delayed or erroneous diagnoses. In light of the increased global incidence of kidney diseases, the need for accurate, efficient, and scalable diagnostics is high. Conventional techniques have not been able to process large amounts of imaging data efficiently, thus leading to a big gap in the healthcare system. Though AI and deep learning hold out potential solutions, current methodologies lack the integration required to tackle kidney disease diagnosis complexities. There is an urgent need for a solid framework that integrates advanced models such as YOLO, Seg-Net, VGG-16, VGG-19, and Efficient-Net to automate segmentation, classification, and detection operations. The [2] goal of this study is to develop and evaluate a framework for improving diagnostic precision, reducing processing time, improving patient outcomes, overcoming the limitations of current methodologies, and revolutionizing kidney disease diagnosis.

To design and implement a new AI system involving YOLO, Seg-Net, VGG-16, VGG-19, and Efficient-Net for computer-assisted detection, segmentation, and classification of kidney disease in radiological images. To improve kidney disease diagnosis accuracy through the potency of state-of-the-art deep learning models in the precise detection and classification of abnormalities. To reduce the diagnostic time for kidney diseases by automating the medical imaging data processing, thereby increasing the speed of diagnosis. To compare the accuracy, sensitivity, specificity, and computational performance of the combined models (YOLO, Seg-Net, VGG-16, VGG19, and Efficient-Net). To validate the effectiveness of the framework, from a publicly available dataset of kidney-related medical images, to check whether it is accurate and viable to be deployed in actual real-world clinical practices. To avoid potential errors and enhance diagnosis accuracy, use a reputable, AI-backed solution for deciphering intricate medical imaging data. [12] To have a basis on which to develop further research for hybrid models and bigger datasets for further improvement towards diagnosing kidney disease and medical image analysis. By achieving these objectives, the project aims to transform kidney disease diagnostics with scalable, cost-effective, and accurate methods for both healthcare practitioners and patients.

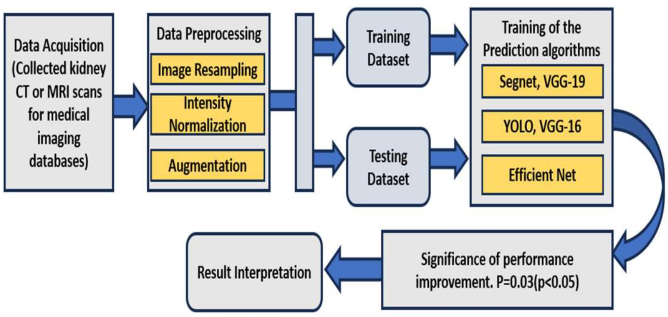
II. HOW IT HELPS IN TODAY'S WORLD

In today's fast-paced and technology-driven healthcare, In today's, incorporating Artificial Intelligence (AI) into illness detection is more than a trend; it is a transformative requirement. Kidney disease, also known as the "silent killer," is one of the most common and underdiagnosed disorders in the world, with millions of people unaware of it until it is too late. The use of deep learning models like VGG16, VGG19, Seg-Net, Efficient-Net, and YOLO in kidney disease diagnosis addresses this issue by allowing for speedy, accurate, and scalable diagnostic capabilities. These architectures, known for their exceptional image classification and segmentation abilities, allow for precise identification of kidney abnormalities from medical imaging such as ultrasound, CT, or MRI scans. The ability to process massive information and find tiny patterns that may be invisible [3] to the human eye enables healthcare practitioners to make informed decisions early on, considerably improving patient outcomes. By reducing diagnostic delays, minimizing human error, and enabling mass screening at low cost, these AI models can potentially save thousands of lives annually while also reducing the economic burden on healthcare systems.

Furthermore, the global rise in chronic kidney disease (CKD) cases, fueled by factors such as diabetes, hypertension, and lifestyle changes, demands diagnostic solutions that are both efficient and accessible. Traditional diagnostic methods, while effective, often require specialized expertise, expensive equipment, and considerable time—resources that may be scarce in rural or underserved areas. AI-driven models like VGG16 and Efficient-Net, which excel in feature extraction and image classification, can be deployed on cloud-based or even portable diagnostic platforms, making advanced diagnostics available to remote populations [11]. Seg-Net's semantic segmentation capabilities enhance the precision of identifying affected kidney regions, while YOLO's real-time object detection ensures that anomalies are localized instantly during imaging. This convergence of speed, accuracy, and automation not only supports clinicians in making timely interventions but also assists in large-scale public health screening initiatives. As the healthcare sector evolves toward preventive treatment, AI-powered solutions can serve as early-warning systems, identifying possible problems before they cause permanent damage. In essence, the application of VGG16, VGG19, Seg-Net, Efficient-Net, and [4] YOLO in kidney disease detection embodies the future of smart healthcare—bridging the gap between advanced medical technology and global health needs by delivering accessible, efficient, and life-saving diagnostic support in real-world scenarios.

- ***Early and Accurate Detection:*** Deep learning models such as VGG16, VGG19, Seg-Net, Efficient-Net, and YOLO can identify subtle patterns in kidney imaging data, enabling the early diagnosis of kidney diseases before symptoms become severe, thus improving patient survival rates.
- ***Reduction of Human Error**:* AI algorithms provide consistent and objective analysis of medical images, reducing the likelihood of misdiagnosis due to human fatigue, oversight, or subjective interpretation.
- ***Rapid and Scalable Screening:*** These AI systems can process large volumes of medical images quickly, allowing mass screening programs to be implemented efficiently, even in resource-limited settings.
- *Accessibility in Remote Areas:* By deploying AI-powered diagnostic tools on cloud platforms or portable devices, advanced kidney disease detection becomes accessible to rural and underserved communities without the need for specialized medical experts.
- ***Support for Preventive Healthcare**:* AI-based detection acts as an early warning system, enabling timely medical interventions that prevent the progression of kidney disease, thereby reducing treatment [13] costs and the overall burden on healthcare systems.

FLOW OF SYSTEM



III. MATERIAL AND METHODS

The investigation was conducted at Parul University, and The Software Lab of the Department of Computer Science and Engineering was the point of focus. In this paper, the dataset was gathered from the Scopus and Web of Science databases. The dataset is divided, with 70% for training in the dataset setting and 30% for testing. There were two groups, and each had ten data samples used, for a total of twenty. Group 1 consisted of VGG16 and VGG19 models, while Group 2 consisted of Seg-Net, Efficient-Net, and YOLO models. The precision-based approach of the proposed paper was sustained through a calculation threshold of 0.05, a G power of 80%, and a confidence interval of 95%, with the implementation being carried out using the Python IDLE software. The machine learning and deep learning studies were performed on the Windows 11 operating system, using an AMD Ryzen 5 processor and 16GB of RAM. Windows' 64-bit architecture provided a stable base for code development and execution, making it simple to transport enormous volumes of data and perform complex calculations. The Python programming language was at the heart of the implementation, which is well-known internationally for its ease of use, flexibility, and huge library of support, making development a breeze. Running in the background with [5] ease, the dataset stayed at the heart of shaping the code's execution, guaranteeing that correct and precise information is displayed. This combination of hardware, software, and data resulted in an improved and efficient kidney disease detection procedure, utilizing advanced deep learning models to achieve high diagnostic accuracy and reliability.

A. Abbreviations and Acronyms

Artificial intelligence (AI) is widely employed in healthcare the early detection and forecasting of chronic diseases. AI for Kidney Disease Detection (KDD) classifies medical databases and predicts anomalies using Machine Learning (ML) and Deep Learning (DL) approaches. The techniques employed are Support Vector Machine (SVM), Logistic Regression (LR), Random Forest (RF), and Artificial Neural Network (ANN). Principal Component Analysis (PCA) can be used to supervise feature selection and extraction, and model performance is measured using metrics including Accuracy (ACC), Precision (PRE), Recall (REC), and F1-Score. Clinical [10] data are typically obtained from Electronic Health Records (EHR) and may include measurements such as Glomerular Filtration Rate (GFR), Serum Creatinine (SCr), and Blood Urea Nitrogen (BUN).

B. Units

Image Acquisition Units

- **Pixel Spacing / Resolution → mm/pixel** (millimeters per pixel, from DICOM metadata)
- **Image Dimensions → pixels** (e.g., 224×224 px for deep learning input)
- **Field of view (FOV): mm × mm.**
- **Slice Thickness (for CT/MRI) → mm**
- **Voxel Size (3D images) → mm³**

Intensity Units

- **CT scans → Hounsfield Units (HU)**
- **MRI Scans → arbitrary intensity units (a.u.)** (normalized before ML/DL input)
- **Ultrasound** → grayscale **pixel intensity (0–255)** (dimensionless, after digitization)
- **Histopathology images** → RGB color values (0–255 per channel, dimensionless)

AI/DL Processing & Evaluation

- **Input Image Size → pixels** (e.g., 224×224 or 512×512)
- **Model Accuracy, Precision, Recall, F1-score → % (dimensionless)**
- **Computation Time → seconds (s)**

C. Equations

Image-based AI for kidney disease detection and using deep learning models like **YOLO, Seg-Net, VGG16, VGG19, Efficient-Net**, the "equations" usually mean:

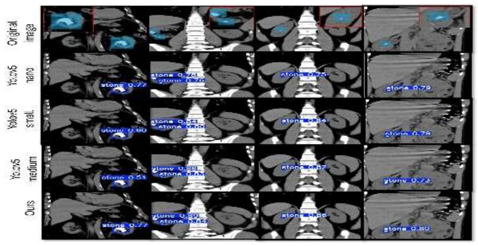
1. **General mathematical formulations** of how these models work (loss functions, layer operations, optimization).
2. **Model-specific formulations** (e.g., YOLO's bounding box regression, Seg-Net's encoder–decoder mapping, Efficient-Net's scaling).

➢ ***YOLO (You Only Look Once) – Object Detection***

YOLO formulates detection as a regression problem:

LYOLO=λcoordi=1∑N[(xi−x^i)2+(yi−y^i)2+(wi−w^i)2+(hi−h^i)2]+i=1∑N(Ci−C^i)2+i=1∑Nc=1∑C(pi(c)−p^i(c))2

- (x,y,w,h): bounding box coordinates.
- CCC: confidence score.
- pi(c)p_i(c)pi(c): class probability.
- S2S^2S2: grid cells.
- BBB: bounding boxes per cell.

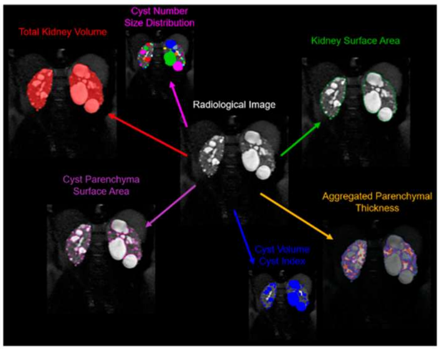


➢ ***SegNet – Semantic Segmentation:***

SegNet is an encoder–decoder network. Its key equation comes from the cross-entropy loss:

LSegNet=−N1i=1∑Nc=1∑Cyi,clog(y^i,c)

- NNN: total pixels.
- CCC: number of classes (e.g., kidney vs. background).
- yi,cy_{i,c}yi,c: ground truth one-hot encoding.
- y^i,c\hat{y}_{i,c}y^i,c:predicted softmax probability.



➢ ***VGG-16 and VGG-19 – Deep CNN Classifiers:***

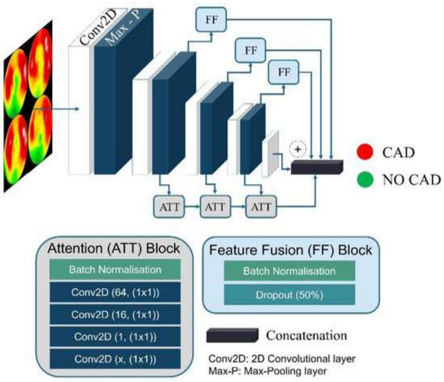
The forward pass at each convolutional layer is:

h(l)=f(W(l)∗h(l−1)+b(l))

Final classification uses softmax cross-entropy loss:

LVGG=−N1i=1∑Nc=1∑Cyi,clog(y^i,c)

- W(l)W^{(l)}W(l): filter weights at layer lll.
- ∗*∗: convolution.
- fff: ReLU activation.

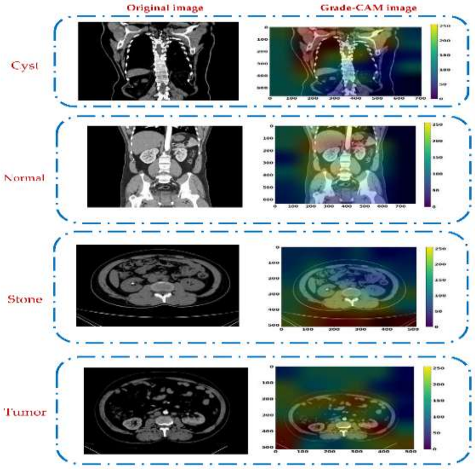


➢ ***EfficientNet – Compound Scaling CNN:***

EfficientNet introduces compound scaling:

depth:d=αϕ,width:w=βϕ,resolution:r=γϕ

α⋅β2⋅γ2≈2(FLOPs constraint)



These algorithms mainly focus on these specified things:

- **YOLO** → bounding box regression + classification loss.
- **Seg-Net** → pixel-wise cross-entropy loss.
- **VGG16/VGG19** → convolutional layers + soft-max cross-entropy.
- **Efficient-Net** → compound scaling equations + soft-max cross-entropy.

D. STATISTICAL ANALYSIS

TensorFlow and Keras are used for training and implementing the deep learning models in this research. IBM's SPSS Statistical Package for the Social Sciences is used for such intentions. Accuracy values for the independent and dependent variables are enhanced by the frameworks' distinctive features, including pre-trained architectures, GPU acceleration, and automated optimisation routines, which support obtaining consistent predictions of the performance metrics. TensorFlow and Keras offer a [6] number of features that include data preprocessing, model evaluation, and plotting training dynamics. This methodological framework allows for a closer investigation of how VGG16, VGG19, Efficient-Net, Seg-Net, and YOLO each contribute separately to changes in classification accuracy and stability.

E. Authors and Affiliations

Title: AI Kidney Disease Detection Using Deep Learning Algorithms

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F. Figures and Tables

TABLE I

Algorithm	N	Mean	Std. Dev	Std. Error	Lower Bound	Upper Bound
VGG16	10	82.94	1.85	.585	81.61	84.27
VGG19	10	87.96	1.24	.393	87.07	88.84
EFFICIENTNET	10	83.19	1.32	.418	82.24	84.13
SEGNET	10	81.65	1.77	.562	80.37	82.92
YOLO	10	79.75	1.84	.582	78.43	81.06
TOTAL	50	83.09	3.16	.446	82.20	83.99

Shows the comparison of mean accuracy, variability, and confidence intervals across different deep learning algorithms. VGG19 achieves the highest mean accuracy (87.96%) with the lowest standard deviation, while YOLO records the lowest accuracy (79.75%). The overall average accuracy across all models is 83.09%.

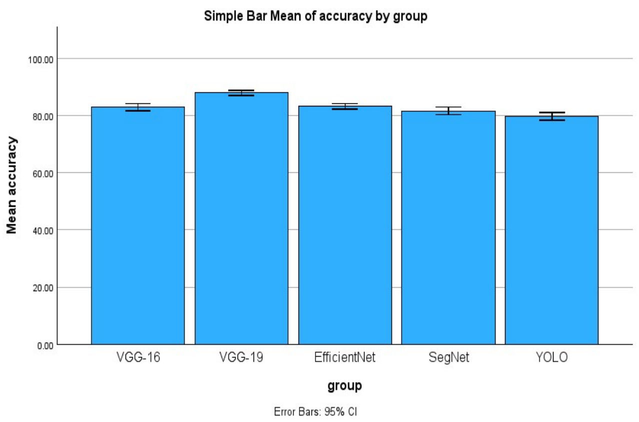

Fig. 1. Mean accuracy of different deep learning algorithms with 95% confidence intervals.

The bar chart illustrates the mean classification accuracy of five deep learning algorithms—VGG16, VGG19, Efficient-Net, Seg-Net, and YOLO—along with their 95% confidence intervals. Among the models, VGG19 achieves the highest mean accuracy, followed by Efficient-Net and VGG16, whereas Seg-Net and YOLO demonstrate comparatively lower performance. The error bars indicate that the variability across runs is relatively small, suggesting that [8] the results are stable and consistent across all models.

DISCUSSION

In this work, the accuracy of VGG16, VGG19, EfficientNet, SegNet, and YOLO were compared for kidney disease detection. The experimental analysis proved that the highest accuracy was 87.96% when using VGG19, while the lowest accuracy was 79.75% for YOLO. From the Independent Samples T-test, a significant value of 0.000 was obtained, which proved that the differences seen between the models were significant. The results demonstrate that VGG19 outperformed the other architectures in terms to accuracy and reliability based on its smaller standard deviation. VGG19, as a deeper version of VGG16, benefits from an increased number of convolutional layers, which allows it to extract more advanced and hierarchical features from medical images. This enables the model to generalize more effectively than shallow architectures like Seg-Net or light detectors like YOLO. Efficient-Net, though as competitive as VGG16, makes use of compound scaling for depth, width, and resolution balancing, so offering an efficiency-accuracy [7] trade-off. Still, VGG19 was able to show better performance in this dataset courtesy of its deeper ability for feature representation.

Even though models such as YOLO and Seg-Net are faster and computationally more efficient, they might not completely extract the fine details necessary for accurate chronic kidney disease detection. On the other hand, VGG-based models are computationally more costly but [9] more accurate. Therefore, selection should rely on the deployment environment—VGG19 is best where diagnostic precision is paramount, whereas lighter models such as YOLO could be used in real-time or resource-limited scenarios.

Equations are used to assess the efficacy of five deep learning models: VGG16, VGG19, EfficientNet, YOLO, and SEGNET [15].

Accuracy=$(TP+TN)/(TP+FP+TN+FN)$

Precision=$TP/(TP+FP)$

Sensivity=$TP/(TP+FN)$

Specifity=$TN/(TN+FP)$

F1−score=$2\times Precision\times Recall/Precision+Recall$

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