CHRONIC KIDNEY DISEASE DETECTION AND CLASSIFICATION USING DEEP LEARNING METHOD – AN EMPIRICAL PROOF

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ABSTRACT

A significant global health issue that is having an impact on healthcare systems is chronic kidney disease, or CKD. Prediction aids in CKD diagnosis, but the interpretability of these models remains challenging for clinicians. Explainable AI (XAI) plays a critical role in addressing this by offering intelligible insights into model predictions. By using deep learning more specifically, the VGG16 architecture instead of traditional machine learning for the identification and categorization of chronic kidney disease, this work advances earlier investigations. The aim is to enhance diagnostic precision and interpretability. Integrating insights from earlier analysis-driven studies, Grad-CAM analysis is incorporated into the deep learning framework. Providing clear and understandable representations of the neural network's decision-making process in medical image data is the aim of this integration. Medical professionals can more accurately classify and interpret images with greater intelligence when Grad-CAM analysis is integrated to highlight important areas in medical images. The discrepancy between the accuracy and interpretability of CKD diagnosis is closed by this study. Our objective is to improve the quality of healthcare worldwide by providing physicians with a useful tool for precisely identifying chronic kidney disease (CKD) by the integration of deep learning techniques and Grad-CAM insights.

Keywords::*Chronic Kidney Disease ,VGG16 ,Grad-CAM, Explainable AI (XAI), Interpretability*

1.INTRODUCTION

Chronic Kidney Disease (CKD) [1] has emerged as a pervasive global health challenge, exerting a significant toll on healthcare systems worldwide. Its prevalence has surged in recent years, amplifying the burden of morbidity, mortality, and healthcare admissions. Notably, this ailment's impact has been disproportionately felt in low-income regions, where resources for detection and treatment are often limited, exacerbating the challenges associated with managing this condition. The escalating prevalence of CKD has underscored the critical need for robust and efficient early detection strategies. Detecting CKD in its nascent stages not only holds the promise of mitigating its progression but also plays a pivotal role in reducing economic burdens and optimizing treatment efficacy. As such, there's an urgent demand for innovative approaches that can address these pressing concerns and revolutionize the landscape of CKD diagnosis and management.

This research represents a pioneering effort aimed at meeting this imperative need by harnessing cutting-edge deep learning

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methodologies, particularly focusing on the VGG16 architecture. While previous studies have made commendable strides in predictive CKD analysis[2], a fundamental challenge persists—the interpretability of models. This lack of interpretability inhibits clinicians' comprehensive understanding of the rationale behind a model's predictions, thus posing a significant barrier to the integration of advanced technologies into clinical practice. Moving beyond traditional machine learning paradigms, this initiative endeavors to refine diagnostic accuracy while ensuring transparent and understandable insights into model decision-making. By amalgamating insights from prior research endeavours, this project integrates advanced deep learning techniques with the innovative Grad-CAM [3](Gradient-weighted Class Activation Mapping) analysis—a visualization method that highlights crucial areas within medical images. This fusion seeks not only to deliver precise and accurate classifications but also to render these interpretations accessible and comprehensible for healthcare professionals.

Aligned with the World Health Organization's emphasis on early disease prevention and intervention strategies, this project represents a concerted effort to integrate Explainable AI (XAI)[4]techniques with state-of-the-art deep learning architectures. The ultimate aim is to provide healthcare professionals with a robust, interpretable, and user-friendly tool for early CKD detection. By doing so, this endeavour seeks to significantly elevate global healthcare standards, particularly in the realm of Kidney health. The significance of this initiative lies in its potential to bridge the gap between complex deep learning models[5] and clinical practice. By augmenting predictive accuracy with interpretability, this project endeavors to empower clinicians with insights into the model's reasoning, fostering trust and understanding of the predictions made. This approach holds immense promise in revolutionizing healthcare practices by leveraging advanced technology that aligns with the expertise and intuition of healthcare professionals.

This endeavor isn't merely a technological advancement; it's a strategic integration of artificial intelligence[6] into the healthcare domain, fostering a symbiotic relationship between machine intelligence and human expertise. Through this collaboration, healthcare professionals can harness the predictive power of deep learning models while retaining control and comprehension over the decision-making process. In the subsequent sections, the methodology deployed in this project will be elaborated upon extensively. This includes a comprehensive elucidation of data preprocessing strategies, the implementation of the VGG16 architecture[7], training and validation protocols, and the integration of Grad-CAM for interpretability enhancement. These methodological intricacies underline the project's multifaceted approach, aimed at delivering a comprehensive solution for early CKD detection and classification, potentially transforming the landscape of Kidney health.

2.RELATED WORK

O. Abumar [8] compares various machine learning models and clustering algorithms using a Kaggle dataset, with Decision Tree achieving the highest classification accuracy at 98.8%. J.Xiao[9] study aims to expedite chronic kidney disease (CKD) severity prediction during follow-up using demographic and blood biochemical features, bypassing the inconvenience of 24-h urinary protein evaluation. Logistic regression exhibited the highest predictive power (AUC 0.873, sensitivity 0.83, specificity 0.82), emphasizing the significance of non-urinary clinical variables, such as ALB, Scr, TG, LDL,and EGFR, in outpatient follow-up for CKD assessment. Ogunleye et al. [10] proposed extreme gradient boosting (XGBoost) algorithm for CKD classification. They used the dataset taken from UCI repository with 25 attributes and achieved 98.7% accuracy. R.Gupta[11] mainly focused on the classification techniques, that is, tree-based decision tree, random forest, and logistic regression has been analysed. Different measure has been used for comparison between algorithms for the dataset collected from standard UCI repository.

R. A.Jeewantha,[12] focused on Chronic Kidney Disease (CKD), identifies Multilayer Perceptron as the most accurate classification method, boasting a remarkable 99.75% accuracy with minimal fluctuation and emphasizing its suitability for bioinformatics and medical science, despite potential computational time considerations. Adeola Ogunleye [13] focuses on the XGBoost algorithm, achieving optimal testing accuracy, sensitivity, and specificity of 1.000. The introduced set-theory-based rule further enhances efficiency, presenting a reduced model with approximately half the features that outperforms individual selection methods, maintaining perfect accuracy, sensitivity, and specificity. G.Stigilic [14] Ensures interpretability in machine learning (ML) models is crucial for facilitating comprehension and explanation of predictions, enabling healthcare experts to make data-driven decisions. The overview distinguishes between personalized and population-level interpretability methods, emphasizing the significance of model-specific and model-agnostic approaches in healthcare applications.

Erico Tjoa [15] Explained about the increasing influence of artificial intelligence and machine learning, particularly in medical applications, necessitates interpretability to ensure transparency and accountability. Despite the challenges posed by the black box nature of deep learning, research reviews categorize interpretability approaches, offering insights for cautious adoption in medical practices and emphasizing the importance of data-based, mathematically grounded medical education. Alejandro Barredo Arrieta [16] reviews the existing literature in Explainable AI (XAI), proposing a novel definition of explainable Machine Learning and providing a taxonomy of contributions for different models, with a focus on Deep Learning.

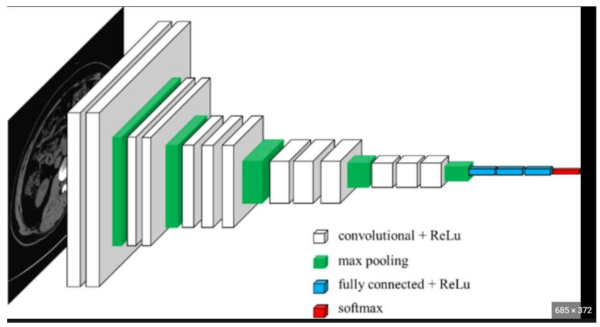
The analysis identifies challenges and emphasizes the importance of Responsible Artificial Intelligence for widespread implementation, aiming to guide newcomers and encourage broader acceptance of AI with a focus on interpretability. While all the observed papers focused primarily on classification[17], detection[18], and the separate use of Explainable AI, this paper not only concentrates on classification and detection but also provides a novel approach by analysing the explainability of the developed prediction model. It offers information on the influence of the selected features in the classification of CKD.

3.METHODOLOGY:

A. Dataset Acquisition and Understanding :

At the onset of this project, an extensive dataset featuring Kidney CT scan images depicting normal, cyst, tumor, and stone conditions was meticulously curated. This dataset, sourced from diverse clinical settings, underwent rigorous selection processes to ensure comprehensive representation across various pathological conditions while adhering to rigorous quality standards. Subsequently, the dataset was segregated into distinct training and validation sets using an 80-20 split, a customary practice in deep learning to facilitate model training and assessment.A thorough comprehension of this dataset's characteristics was paramount. Detailed analyses were conducted to understand critical aspects such as class distribution, image resolutions, and potential biases. This meticulous approach aimed to uncover and rectify any imbalances, anomalies, or inconsistencies within the dataset that might impede the model's performance. This phase focused on establishing a robust dataset preparation process, laying the foundation for subsequent deep learning model development, prioritizing dataset integrity and reliability.

B. Model Architecture Selection and Development (VGG16 Model) :



Selecting an appropriate deep learning architecture significantly influences the project's outcome. In this project, the VGG16 architecture was chosen as the primary model due to its proven efficacy in image classification tasks. The VGG16 architecture, introduced by the Visual Graphics Group at Oxford, is renowned for its simplicity and effectiveness. It consists of 16 weight layers, including 13 convolutional layers and 3 fully connected layers. The convolutional layers are comprised of 3x3 convolutional filters, with max-pooling layers interspersed between them to downsample the spatial dimensions, capturing hierarchical features from the input images.

The pre-trained VGG16 model, originally trained on the ImageNet dataset, possesses a robust ability to extract intricate patterns and features from images. Leveraging transfer learning, the pre-trained VGG16 model serves as a feature extractor. The learned features from the VGG16 architecture are utilized as a foundation for understanding and recognizing patterns within Kidney CT scan images relevant to chronic kidney disease (CKD). In this project, the initial layers of VGG16 remain frozen, preserving the learned features and weights acquired during ImageNet training. Subsequently, the last few layers are fine-tuned or retrained using the CKD dataset. This process adapts the VGG16 architecture to specifically identify CKD-related patterns, enhancing the model's performance in

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classifying Kidney CT scan images into categories such as normal, cyst, tumor, or stone.

The utilization of VGG16 for CKD classification involves the input of images into the network, where each image propagates through the layers of the neural network. The initial layers of VGG16 capture low-level features like edges and textures, while the deeper layers discern higher-level features and complex patterns related to CKD conditions. These features are then utilized to make predictions regarding the specific class or condition of the Kidney CT scan images. Visualizing the architecture of VGG16 involves illustrating its layers and their connections, providing a comprehensive overview of how the input data progresses through the network, extracting essential features at various stages. This visual representation aids in comprehending the model's inner workings, facilitating a deeper understanding of how the network learns and makes predictions based on the learned features.

C. Model Training and Validation: Refining Neural Networks for CT Scan Image Classification

Kicking off the training phase, the VGG16 architecture digests meticulously pre-processed datasets of kidney CT scan images to educate its neural networks. This iterative process unfolds across multiple epochs, allowing the model to progressively refine its internal parameters. The primary aim is to enhance the model's ability to discern intricate patterns and features within the images, ensuring accurate classification into normal, cyst, tumor, or stone categories. Critical considerations in this phase revolve around fine-tuning key hyperparameters. The learning rate, a crucial factor dictating parameter optimization's step size, undergoes precise adjustments to strike an optimal balance between convergence speed and accuracy. Simultaneously, optimizing the batch size—determining the number of samples processed before updating model parameters—serves to streamline computational efficiency and model convergence. The choice of optimizers, such as Adam or RMSprop, is also scrutinized to enhance the neural network's learning dynamics.

The validation set plays a pivotal role throughout the training regimen. Set apart from the training data, this validation dataset functions as an independent benchmark. Here, the model continuously evaluates its performance during training, scrutinizing metrics like accuracy, loss, and other key indicators. This ongoing validation acts as a guard against overfitting—a situation where the model tailors itself excessively to the training data's nuances, potentially compromising its performance on new, unseen data. Regular validation checks during training facilitate fine-tuning of model parameters or the implementation of early stopping strategies to maintain optimal performance without succumbing to overfitting. Balancing model complexity and generalization proves instrumental in ensuring robust performance on unseen kidney CT scan images, pivotal for the model's real-world applicability beyond the boundaries of the training dataset.

D. Integrating Interpretability through Grad-CAM: Bridging Model Predictions and Clinical Insights

In the pursuit of robust medical AI systems, achieving not only high predictive accuracy but also interpretability stands as a crucial milestone. To fortify the interpretability facet within this project, Grad-CAM (Gradient-weighted Class Activation Mapping) emerges as a potent tool integrated into the convolutional neural networks (CNNs). Grad-CAM serves as an interpretability aid, unravelling the intricate decision-making of the CNNs by generating heatmaps. These heatmaps spotlight the precise regions within kidney CT scan images that significantly influence the model's classification decisions. By visually accentuating these regions, Grad-CAM facilitates an intuitive understanding of the CNN's focus areas, rendering complex model decisions accessible and comprehensible to clinicians.

The fundamental advantage lies in its ability to bridge the gap between sophisticated model computations and actionable clinical insights. Through these heatmaps, clinicians gain transparency into the neural network's decision process, effectively transforming AI-driven predictions from opaque black boxes into transparent, interpretable insights. The integration of Grad-CAM augments the model's reliability and utility in real-world clinical settings. Its interpretability fosters trust among medical practitioners, empowering them to comprehend and potentially validate the AI-driven predictions. This collaborative synergy between advanced AI algorithms and clinical expertise bolsters the prospects of seamlessly integrating AI insights into medical decision-making processes, ultimately enhancing patient care and diagnostics in kidney-related ailments.

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E. Model Evaluation

The classification report and accuracy metrics provide a comprehensive evaluation of the model's performance in categorizing different classes within the dataset. The accuracy of 98% signifies the model's overall correct prediction rate across all classes, indicating a high level of precision in its classifications.

The classification report breaks down the model's performance per class, detailing metrics such as precision, recall, and F1-score. Precision signifies the proportion of correctly predicted instances among the predicted positive cases for each class. Recall represents the ratio of correctly predicted instances among the actual positive cases. F1-score, the harmonic mean of precision and recall, provides a balanced measure between the two metrics. Additionally, the confusion matrix offers a visual representation of the model's performance by tabulating actual classes against predicted classes. It illustrates true positive, true negative, false positive, and false negative predictions for each class, aiding in understanding the model's specific strengths and weaknesses in differentiating between classes

4.RESULTS AND DISCUSSION

The model achieved an impressive overall accuracy of 98% in classifying CKD categories, highlighting its effectiveness in detecting kidney-related ailments. This high accuracy is pivotal for early intervention and improved patient outcomes, underscoring the significance of robust diagnostic tools in healthcare. Precision, recall, and F1-score metrics provided detailed insights into the model's performance per class. Precision measures the proportion of correctly predicted instances among the predicted positive cases for each class, indicating the model's ability to accurately identify specific CKD conditions. Similarly, recall signifies the ratio of correctly predicted instances among the actual positive cases, demonstrating the model's sensitivity to detecting true positive cases.

The F1-score provides a fair assessment of the model's effectiveness across all classes since it is the harmonic mean of precision and recall. This measure is especially useful in situations where striking a balance between recall and precision is crucial to accurately identifying positive cases and minimising false positives.

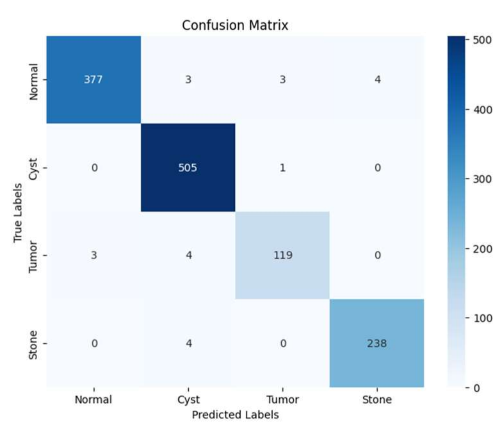
The visual representation of the model's performance, the confusion matrix, allowed for a deeper understanding of its unique advantages and disadvantages in terms of CKD category differentiation. Clinicians can improve the diagnosis accuracy of the model by identifying patterns of misclassification through analysis of the confusion matrix and making necessary adjustments to the model.

All things considered, the findings show how well the VGG16 architecture works with Grad-CAM to provide interpretable CKD diagnosis. The model achieves high predicted accuracy and gives doctors transparent insights into its decision-making process by incorporating Explainable AI approaches. The combination of cutting-edge AI algorithms with clinical knowledge in this joint method has great potential to revolutionise the diagnosis and treatment of chronic kidney disease (CKD), ultimately improving healthcare outcomes worldwide.

Model Evaluation: Classification Report
Accuracy:98%

CLASS	PRECISION	RECALL	F1-SCORE
NORMAL	1.00	0.99	0.99
CYST	1.00	0.96	0.98
TUMOUR	0.86	1.00	0.93
STONE	0.97	0.99	0.98

CONFUSION MATRIX



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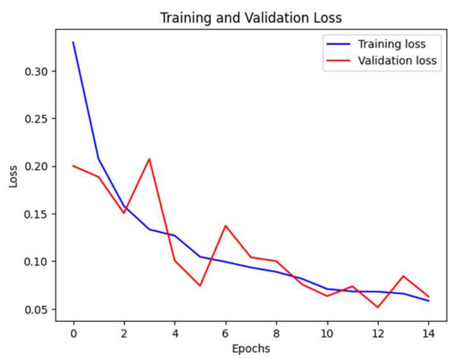
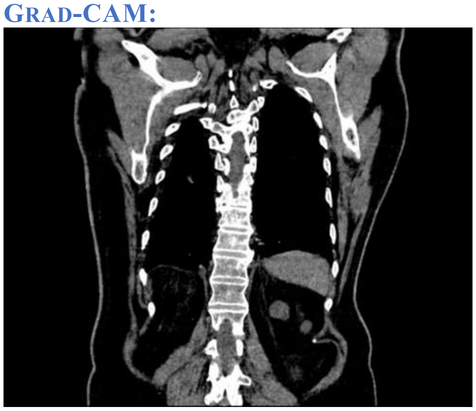
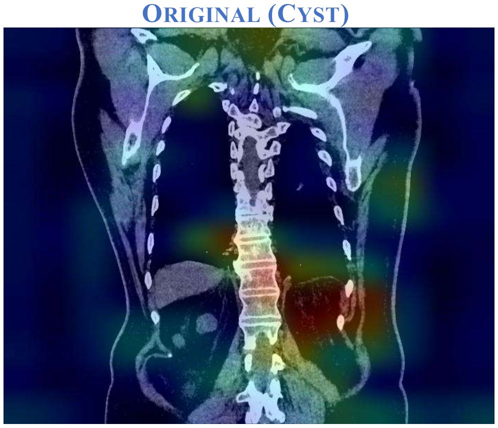


GRAD-CAM:



ORIGINAL (CYST)



GRADIENT MAPPED (CYST)

5. CONCLUSION

Our research successfully harnessed cutting-edge deep learning, merging the power of VGG16, a sophisticated image analysis tool with Grad-CAM, which sheds light on how the AI reaches its conclusions. This fusion enabled accurate classification of kidney conditions from CT scan images. VGG16, known for its ability to understand complex image patterns, was fine-tuned to identify normal, cyst, tumour, and stone conditions. What makes our project unique is Grad-CAM, which generates colour-highlighted areas in images, aiding doctors in understanding the AI's decision-making process. This interpretability helps build trust in the AI's diagnoses. Our achievement isn't just about accuracy, it's about providing transparent tools for diagnosing kidney conditions. This intersection of technology and healthcare promises a future where AI supports medical expertise, ensuring more accurate and understandable diagnoses.

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