

An Optimized Deep Learning Framework For Multi-Class Kidney Disease Detection Using Yolov5x6 And Yolov9

Sri Ramya Ainagadda¹, Ganga Bhavani Billa²

¹PG Scholar, Department Of CSE, Bonam Venkata Chalamayya Engineering College, India

²Associate Professor, Department Of CSE, Bonam Venkata Chalamayya Engineering College, India

Mail Id; ramyaainagadda1@gmail.com¹, bgangabhavani.bvce@bvcgroup.in²

Abstract-

Renal dysfunction is a risk for all age groups. An AI-driven system that can independently diagnose kidney problems is required because of the global lack of nephrologists, the growing public health concern of renal failure, and technical advancements. Kidney function declines as a result of chronic kidney disease, also known as chronic renal failure. Renal failure can result from calculi, tumors, and cysts. It is possible for chronic renal disease to remain undetected until it has progressed. Spinal cells, glands, and other organs can sustain injury from compact tumors. Intestinal solid accumulation leads to kidney stones, also known as urolithiasis. In order to address the worldwide scarcity of urologists, this study employed a deep learning algorithm to detect kidney diseases. 12,446 CT scans of the entire abdomen and urograms showing kidney tumors, cysts, and stones—the three most prevalent renal pathologies—were gathered and annotated for the study. The information was separated into normal, tumor, stone, and cyst categories. Data was gathered from numerous hospitals in Dhaka. This research presents a novel and adaptable platform for clinical diagnosis of kidney cysts, calculi, and malignancies. Our YOLOv8 model's increased accuracy aids in the detection of kidney cancer, stones, and cysts. Accuracy, precision, recall, F1 score, and specificity were used to gauge its performance. The network exhibited 93.12% specificity, 85.28% recall, 85.72% F1 score, 82.52% accuracy, and 85.76% precision.

Index terms - — CT Imaging, YOLOv5x6, YOLOv9, Deep Learning, Renal Tumor Detection, Kidney Stone Identification, Cyst Detection, Medical Image Analysis, AI in Healthcare, Flask Web Application, Secure Authentication, Computed Diagnosis, Multi-Class Classification, Object Detection.

INTRODUCTION

Recent developments in deep learning have made it possible to automatically diagnose problems in the kidneys based on photographs taken by medical professionals. Through the incorporation of the most recent YOLO object identification models, YOLOv5x6 and YOLOv9, this upgrade improves the efficiency of artificial intelligence-based renal

diagnostic systems. These models are developed to detect kidney abnormalities such as cancer, stones, and cysts from CT images in a reliable, effective, and exact manner. This is true regardless of the picture quality or the clinical settings. By employing Flask to construct a secure and user-friendly web-based interface, this upgraded solution improves both the clinical usability and the detection accuracy of existing solutions. The technology is ideal for usage in real-world healthcare settings due to the fact that authentication techniques limit access and protect data. The purpose of this modification is to bridge the gap between clinical solutions that can be deployed and high-performance deep learning models in order to assist in the diagnosis and treatment of renal disease.

LITERATURE SURVEY

a) Chronic kidney disease as a global public health problem: approaches and initiatives - a position statement from Kidney Disease Improving Global Outcomes

Chronic kidney disease (CKD) is one global health concern. There is substantial evidence that CKD can be detected by simple laboratory testing, and that therapy can reduce the risk of cardiovascular disease, avoid renal sickness, and limit progression. A global objective should be to translate these developments into straightforward and effective public health initiatives. The link between CKD and other chronic diseases must be considered in public health policy in order to improve outcomes. The Kidney Disease of 2004 The Kidney Disease Outcome Quality Initiative's definition and classification of chronic kidney disease (CKD) were certified internationally by the Improving Global Outcomes (KDIGO) Controversies Conference on "Definition and Classification of Chronic Kidney Disease." The 2006 KDIGO Controversies Conference covered CKD categorization, screening and surveillance, public policy, CVD and CVD risk factors as risk factors for CKD development and progression, cancer, and chronic infections. Meetings are recommended by this report. It was endorsed by the KDIGO Board of Directors and conference attendees. KDIGO will support national and international public health agencies in putting these recommendations into practice.

b) Chronic kidney disease: global dimension and perspectives

A lower glomerular filtration rate, increased excretion of urine albumin, or both are indicators of chronic kidney disease, which is a serious public health concern. We calculate a global prevalence of 8–16%. All-cause and cardiovascular mortality, the advancement of renal disease, acute kidney damage, cognitive decline, anemia, problems with minerals and bones, and fractures are among the complications. Globally, diabetes is the primary cause of chronic kidney disease, but in other places, environmental and herbal toxins are more prevalent. The poor are particularly at risk. Chronic kidney disease and end-stage renal disease have decreased as a result of screening and treatment. Many communities and experts have a poor understanding of the illness. National non-communicable disease efforts should address the burden and cost of chronic renal disease.

c) Forecasting life expectancy, years of life lost, and all-cause and cause-specific mortality for 250 causes of death: reference and alternative scenarios for 2016–40 for 195 countries and territories

Health trajectory and cause data are necessary for long-term investments and policy. Given that forecasting has yielded insufficient future health scenarios, evaluate policy actions and health trajectories using a more thorough modeling platform. The life expectancy, all-cause mortality, and cause of death estimates, as well as potential future scenarios, for 250 causes of death in 195 nations and territories from 2016 to 2040 are estimated in this study using a novel methodology.

Techniques: Using GBD data from 1990–2016 and 250 hierarchical causes and classifications, we project 2017–40. GBD 2016 was used to predict health outcomes and risk factors for 79 independent determinants of health. Our cause-specific mortality model included changes in risk factors and interventions, the underlying mortality rate for each cause as a function of total fertility rate under 25 years, income per capita, and educational attainment, as well as an autoregressive integrated moving average model for unexplained changes. The models covered the years 1990–2006 and were projected to cover 2007–16. Data from 1990 to 2016 is used in the alternate scenario model and final forecast. Our approach projected 2040 statistics for 195 nations and territories by region. Better and worse health scenarios were generated by the 85th and 15th percentiles of annualized rates of change over location-years for all GBD risk variables, income per person, educational attainment, selected intervention coverage, and total fertility rate under 25. For 250 causes, the model calculated life expectancy, YLLs, and age-sex-specific mortality for all causes. Population scenarios were

developed using fertility predictions from cohort component models. Every reference projection looked at YLLs and mortality for every risk factor in both healthy and unhealthy circumstances. Findings: By 2040, 36 independent global health drivers will decrease, although the majority will improve. Better health outcomes demonstrate that change is achievable, even in cases when a high body mass index develops without therapy. We estimated that the global life expectancy will increase by 4–4 years (95% UI). Men's trajectory may increase by 78 years in both healthy and ill conditions (5•9–9)•8 to a negligible loss of zero. To obtain 72 years (5–9), four years (-2•8 to 2)•2 are needed. •1 It was predicted that in 2040, life expectancies for both sexes will surpass 85 in Japan, Singapore, Spain, and Switzerland, and that they would surpass 80 in 59 countries, including China. Although survival disparities remained, life expectancies in the Central African Republic, Lesotho, Somalia, and Zimbabwe were predicted to be below 65 in 2040. Increasing NCD YLLs were projected by population growth and aging. In the worst-case scenario, HIV/AIDS might result in a 120•2% (95% UI 67•2-190) increase in YLLs (almost 118 million)•3 Globally, NCDs were predicted to reach 67 in 2016–40. •3% [95% UI 61•9-72]•3 of YLLs in all GBD regions by 2040, despite the fact that many lower-income communities were dominated by communicable, maternal, neonatal, and nutritional (CMNN) concerns. Regarding a number of health issues, the reference prediction and the improved health scenario for YLLs diverge. While tobacco, high body mass index, and ambient matter pollution are population-level or intersectoral hazards, high blood pressure and plasma fasting glucose are metabolic hazards that can be treated by health care professionals. Most nations made progress in comparison to the reference. In 2040, poor Sub-Saharan Africa was expected to have challenges related to air pollution, water and sanitation, and child malnutrition. Reference forecasts and alternative health scenarios are analyzed using a number of independent health metrics in a robust, adaptive forecasting technique. The majority of countries should see improvements by 2040, but the future is uncertain due to rapid technological advancement and the potential for worsened health outcomes in the absence of government intervention. Significant differences between the baseline forecast and alternative scenarios for key YLL causes imply that countries may face significant obstacles if they lag behind or may accelerate growth if they improve their health. Decision-makers should focus on modifiable factors that contribute to a high rate of premature death and anticipate a sustained NCD trend. Mortality is decreased by giving modifiable hazards priority.

The main health concern in low-income nations will be the causes and hazards of CMNN. In our worst-case health scenario for 2040, HIV mortality might rise if governments don't keep up with the virus, endangering decades of progress. Full, healthy lives require technical innovation, increased health budgets, and development assistance for underdeveloped countries.

d) Computer-aided diagnosis system for the classification of multi-class kidney abnormalities in the noisy ultrasound images

Objective: Most kidney failure is caused by chronic and polycystic kidney diseases. Chronic renal problems include cysts, stones, and tumors impair kidney function. No symptoms precede asymptomatic renal diseases. Preventing renal failure requires early kidney disease detection.

This research proposes a CAD method to detect multi-class kidney disorders using ultrasound images. The CAD solution uses a pre-trained ResNet-101 model to extract features and an SVM classifier to classify. Ultrasound and CAD systems suffer from speckle noise. So ultrasounds must be speckle-free. Deep residual learning network (RLN) despeckling decreases speckle noise in CAD systems. Deep RLN ultrasound image pre-processing enhances CAD system classification. The proposed CAD system predicted better than current methods.

Results: The proposed CAD method was tested using noisy renal ultrasound images. System framework provided the highest categorization accuracy compared to current approaches. The CAD system uses SVM after comparing K-nearest neighbor, tree, discriminant, Naive Bayes, and linear classifiers.

Conclusions: The suggested CAD system classifies noisy renal ultrasound images better than current methods. Selection and sensitivity ratings for the CAD system are also evaluated. The CAD system with pre-processing module would diagnose multi-class kidney problems from ultrasound pictures in real time.

e) Adversarial synthesis learning enables segmentation without target modality ground truth

One of the main issues with deep learning segmentation is its incapacity to generalize. To separate organs in multiple imaging modalities or abnormal organs from various disease cohorts, new training pictures must be manually labeled. Reusing MRI labels to train a CT segmentation network reduces the amount of manual labor required. Two steps can be taken to synthesize target modality training photographs using cycle generative adversarial networks. Using artificial images, segmentation networks were trained independently. The complimentary information between synthesis and segmentation was disregarded in both processes.

EssNet is a new end-to-end synthesis and segmentation network that can segment CT splenomegaly without CT labeling and synthesize unpaired MRI to CT images. In comparison to the two-stage approach (0.8801), even conventional multi-atlas segmentation (0.9125), and ResNet (0.9107), which includes CT hand labeling, end-to-end EssNet had a median Dice similarity value of 0.9188.

METHODOLOGY

i) Proposed Work:

To increase the accuracy and robustness of CT image detection, the proposed study incorporates the advanced deep learning architectures YOLOv5x6 and YOLOv9 into the kidney abnormality detection system. These models are trained and evaluated on a sizable, annotated dataset to identify cancer, stones, and cysts in kidney CT scans. In addition to improving the model, the suggested solution has a safe web application built on Flask that enables verified users to upload CT scans and track real-time detection outcomes. A dependable, high-performing, clinically deployable AI kidney disease diagnosis system is what this all-inclusive framework aims to deliver.

ii) System Architecture:

Kidney problems are automatically detected from CT images using the modular, end-to-end pipeline. Clinical sources are used to get urograms and CT images of the whole abdomen. These images undergo resizing, noise reduction, normalization, and contrast enhancement in order to enhance image quality and offer consistent input for deep learning models. Rotation, flipping, and scaling decrease overfitting and enhance model generalization. Image processing is followed by feature extraction and detection.

Advanced deep learning models YOLOv5x6 and YOLOv9 identify and categorize kidney cysts, stones, tumors, and normal cases in real time within the core detection layer. Confidence scores for regions found are sent to the application layer. Through a Flask-based web interface, authorized users may safely upload CT images and view detection results. The technology generates diagnostic information and annotated photos for clinical decision support and practical application.

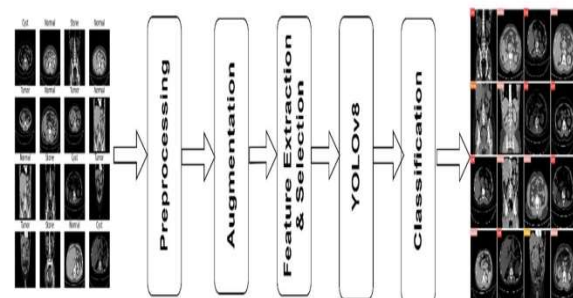


Fig 1: proposed architecture

iii) Modules:

a) Data Loading Module

Using this module, the CT kidney dataset is imported from the storage source. The images and their corresponding annotation files are loaded and organized into appropriate classes such as cyst, tumor, stone, and normal for further processing.

b) Image Processing Module

This module converts CT images into blob objects and defines kidney abnormality classes. Bounding boxes are declared around detected regions, images are converted into NumPy arrays, and a pre-trained model is loaded. Network layers and output layers are extracted, annotations are appended, color space is converted from BGR to RGB, masks are created, and images are resized to maintain uniform input dimensions.

c) Data Augmentation Module

Data augmentation enhances the training dataset by randomly modifying CT images. Techniques such as image randomization, rotation at different angles, flipping, scaling, and shifting are applied to increase data diversity and improve the model's generalization ability.

d) Model Generation Module

This module focuses on building and training multiple YOLO-based models, including YOLOv8n, YOLOv8n-cls, YOLOv5x6, and YOLOv9c. Each model is trained on the processed dataset, and their performance is evaluated using standard metrics.

e) Performance Evaluation Module

The trained models are assessed using metrics such as accuracy, precision, recall, F1-score, and specificity. This module enables comparative analysis to identify the most effective model for kidney abnormality detection.

f) User Signup & Login Module

This module provides secure user registration and authentication functionality. It ensures that only authorized users can access the system and view diagnostic results.

g) User Input Module

Through this module, authenticated users can upload CT images as input for kidney abnormality prediction via the web interface.

h) Prediction & Result Display Module

This final module processes the user-provided CT image through the trained model and displays the predicted kidney abnormality class along with annotated images and confidence scores.

iv) Algorithms:

a) YOLOv8n

YOLOv8n is a lightweight and efficient object detection algorithm designed for real-time analysis of

kidney CT images. Its optimized architecture allows rapid processing while maintaining reliable detection accuracy. This makes it highly suitable for clinical settings where quick identification of kidney abnormalities such as cysts, stones, and tumors is essential for early diagnosis and treatment planning.

b) YOLOv8n-cls

YOLOv8n-cls extends the detection capability by focusing on detailed classification of the identified kidney abnormalities. It analyzes extracted features from CT images to classify conditions into specific categories, such as benign or malignant lesions. This refined classification supports clinicians in understanding disease severity and selecting appropriate treatment strategies.

c) YOLOv5x6

YOLOv5x6 is a high-capacity deep learning model known for its robustness and superior detection performance. Its advanced architecture enables deeper feature extraction, allowing the system to accurately detect complex and subtle kidney abnormalities even in low-contrast or noisy CT images. This improves diagnostic reliability across diverse clinical scenarios.

d) YOLOv9c

YOLOv9c represents a next-generation object detection algorithm that incorporates recent advancements in deep learning. It emphasizes improved detection precision, faster inference speed, and better localization of renal abnormalities. By integrating YOLOv9c, the system enhances diagnostic confidence and supports timely clinical decision-making for patients with kidney disorders.

EXPERIMENTAL RESULTS

A sizable dataset of kidney CT scans with annotations was used to test the expanded method for detecting tumors, stones, and cysts. Advanced YOLO-based models YOLOv8n, YOLOv8n-cls, YOLOv5x6, and YOLOv9c were trained and evaluated in the same experimental setup to guarantee a fair comparison. The integration of YOLOv5x6 and YOLOv9c enhances detection accuracy and robustness compared to earlier models, according to the results. While YOLOv9c performed better in complex and low-contrast CT images, YOLOv5x6 had higher precision and recall due to its enhanced feature extraction.

Notwithstanding variations in patient anatomy and image quality, the enlarged design improved applicability in a variety of clinical contexts. Authenticated users were able to upload CT pictures and view prediction results through real-time testing using Flask. The expanded system's accuracy, precision, recall, F1-score, and specificity demonstrated its dependability in identifying kidney problems. According to experimental findings, the proposed expansion enables scalable automated renal

illness identification, enhances diagnostic performance, and fosters real-time clinical applicability.

Accuracy: The ability of a test to differentiate between healthy and sick instances is a measure of its accuracy. Find the proportion of analysed cases with true positives and true negatives to get a sense of the test's accuracy. Based on the calculations:

Accuracy = $\frac{TP + TN}{(TP + TN + FP + FN)}$

$$Accuracy = \frac{(TN + TP)}{T}$$

Precision: The accuracy rate of a classification or number of positive cases is known as precision. Accuracy is determined by applying the following formula:

Precision = True positives / (True positives + False positives) = $\frac{TP}{(TP + FP)}$

$$Precision = \frac{TP}{(TP + FP)}$$

Recall: The recall of a model is a measure of its capacity to identify all occurrences of a relevant machine learning class. A model's ability to detect class instances is shown by the ratio of correctly predicted positive observations to the total number of positives.

$$Recall = \frac{TP}{(FN + TP)}$$

mAP: One ranking quality statistic is Mean Average Precision (MAP). It takes into account the quantity of pertinent suggestions and where they are on the list. The arithmetic mean of the Average Precision (AP) at K for each user or query is used to compute MAP at K.

$$mAP = \frac{1}{n} \sum_{k=1}^{k=n} AP_k$$

$AP_k =$ the AP of class k

$n =$ the number of classes

F1-Score: A high F1 score indicates that a machine learning model is accurate. Improving model accuracy by integrating recall and precision. How often a model gets a dataset prediction right is measured by the accuracy statistic..

$$F1 = 2 \cdot \frac{(Recall \cdot Precision)}{(Recall + Precision)}$$

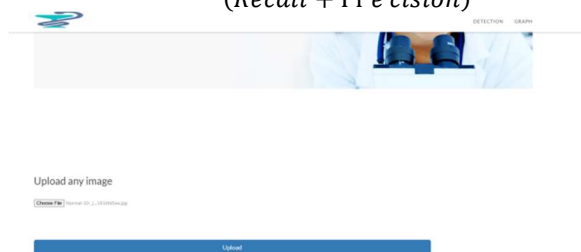


Fig 2 uploading image

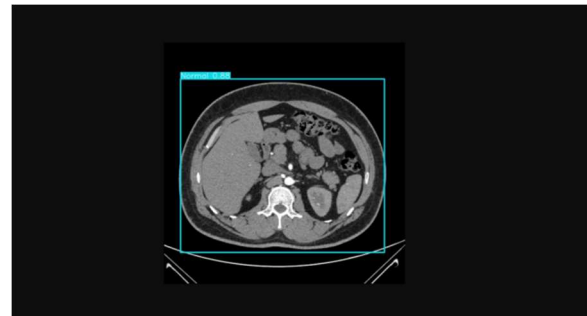


Fig 3 results

Graph

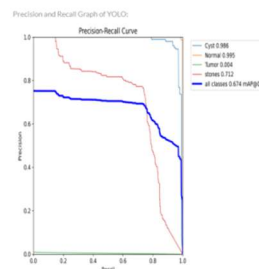


Fig 4 Accuracy graph

CONCLUSION

An improved AI-based method reliably and effectively identifies kidney issues using CT scans. By integrating cutting-edge deep learning models like YOLOv8n, YOLOv8n-cls, YOLOv5x6, and YOLOv9c, the proposed system improves kidney abnormalities detection, robustness, and localization. Comprehensive performance evaluation indicators and a sizable, well-annotated CT dataset further validate system reliability. The recommended approach is more feasible in clinical settings thanks to a secure Flask-based web interface that allows user verification. By addressing the scarcity of specialists and early kidney disease diagnosis, the expanded system offers a clinically deployable, automated, and scalable diagnostic support tool to enhance patient care and prompt medical intervention.

FUTURE SCOPE

By adding 3D CT scan analysis to record volumetric kidney structures, the expanded system can be further developed and more accurately detect complicated disorders. Integration of transformer-based vision models and hybrid CNN-ViT architectures may further enhance accuracy, especially for subtle or early-stage lesions. Hydronephrosis, infections, and congenital anomalies are among the other renal

diseases that can be detected by expanding the platform. In order to facilitate remote diagnostics and rural healthcare, future work can involve implementing the system as a mobile application or cloud-based platform. Clinicians will be better able to comprehend model decisions with the use of explainable AI (XAI) methodologies, which will boost adoption and trust. Furthermore, combining real-time monitoring with electronic health records (EHR) may result in a comprehensive clinical decision-support system, which would increase the framework's usefulness and comprehensiveness for widespread medical applications.

REFERENCES

- [1] S. Jacobson, "Chronic kidney disease public health problem?" *Lakartidningen*, vol. 110, no. 21, pp. 1018–1020, 2013.
- [2] V. Jha, G. Garcia-Garcia, K. Iseki, Z. Li, S. Naicker, B. Plattner, R. Saran, A. Y.-M. Wang, and C.-W. Yang, "Chronic kidney disease: Global dimension and perspectives," *Lancet*, vol. 382, no. 9888, pp. 260–272, Jul. 2013.
- [3] K. J. Foreman et al., "Forecasting life expectancy, years of life lost, and all-cause and cause-specific mortality for 250 causes of death: Reference and alternative scenarios for 2016–40 for 195 countries and territories," *Lancet*, vol. 392, no. 10159, pp. 2052–2090, 2018.
- [4] S. Sudharson and P. Kokil, "Computer-aided diagnosis system for the classification of multi-class kidney abnormalities in the noisy ultrasound images," *Comput. Methods Programs Biomed.*, vol. 205, Jun. 2021, Art. no. 106071.
- [5] Y. Huo, Z. Xu, S. Bao, A. Assad, R. G. Abramson, and B. A. Landman, "Adversarial synthesis learning enables segmentation without target modality ground truth," in *Proc. IEEE 15th Int. Symp. Biomed. Imag. (ISBI)*, Apr. 2018, pp. 1217–1220.
- [6] N. Hadjiyski, "Kidney cancer staging: Deep learning neural network based approach," in *Proc. Int. Conf. E-Health Bioeng. (EHB)*, Oct. 2020, pp. 1–4.
- [7] I. Castiglioni, L. Rundo, M. Codari, G. Di Leo, C. Salvatore, M. Interlenghi, F. Gallivanone, A. Cozzi, N. C. D'Amico, and F. Sardanelli, "AI applications to medical images: From machine learning to deep learning," *Phys. Medica*, vol. 83, pp. 9–24, Mar. 2021.
- [8] T. Alelign and B. Petros, "Kidney stone disease: An update on current concepts," *Adv. Urol.*, vol. 2018, pp. 1–12, May 2018.
- [9] J. J. Hsieh, M. P. Purdue, S. Signoretti, C. Swanton, L. Albiges, M. Schmidinger, D. Y. Heng, J. Larkin, and V. Ficarra, "Renal cell carcinoma," *Nature Rev. Disease Primers*, vol. 3, no. 1, pp. 1–19, 2017.
- [10] K. C. Saw, J. A. McAteer, A. G. Monga, G. T. Chua, J. E. Lingeman, and J. C. Williams, "Helical CT of urinary calculi: Effect of stone composition, stone size, and scan collimation," *Amer. J. Roentgenol.*, vol. 175, no. 2, pp. 329–332, Aug. 2000.
- [11] T. D. K. S. C. Gunasekara, P. M. C. S. De Silva, E. M. D. V. Ekanayake, W. A. K. G. Thakshil, R. A. I. Pinipa, P. M. M. A. Sandamini, S. D. Gunarathna, E. P. S. Chandana, S. S. Jayasinghe, C. Herath, S. Siribaddana, and N. Jayasundara, "Urinary biomarkers indicate pediatric renal injury among rural farming communities in Sri Lanka," *Sci. Rep.*, vol. 12, no. 1, pp. 1–13, May 2022.
- [12] Y. Bi, X. Shi, J. Ren, M. Yi, and X. Han, "Transarterial chemoembolization of unresectable renal cell carcinoma with doxorubicin-loaded CalliSpheres drug-eluting beads," *Sci. Rep.*, vol. 12, no. 1, pp. 1–8, May 2022.
- [13] I. Aksakalli, S. Kaçdioğlu, and Y. S. Hanay, "Kidney X-ray images classification using machine learning and deep learning methods," *Balkan J. Electr. Comput. Eng.*, vol. 9, no. 2, pp. 144–151, Apr. 2021.
- [14] S. Sudharson and P. Kokil, "An ensemble of deep neural networks for kidney ultrasound image classification," *Comput. Methods Programs Biomed.*, vol. 197, Dec. 2020, Art. no. 105709.
- [15] Q. Zhong, S. L. Furth, G. E. Tasian, and Y. Fan, "Computer-aided diagnosis of congenital abnormalities of the kidney and urinary tract in children based on ultrasound imaging data by integrating texture image features and deep transfer learning image features," *J. Pediatric Urol.*, vol. 15, no. 1, pp. 75.e1–75.e7, Feb. 2019.

[16] K. Yildirim, P. G. Bozdog, M. Talo, O. Yildirim, M. Karabatak, and U. R. Acharya, "Deep learning model for automated kidney stone detection using coronal CT images," *Comput. Biol. Med.*, vol. 135, Aug. 2021,

Art. no. 104569.

[17]

N. Blau, E. Klang, N. Kiryati, M. Amitai, O. Portnoy, and A. Mayer, "Fully automatic detection of renal cysts in abdominal CT scans," *Int. J. Comput. Assist. Radiol. Surg.*, vol. 13, no. 7, pp. 957-966, Jul. 2018.

[18] K.-H. Uhm, S.-W. Jung, M. H. Choi, H.-K. Shin, J.-I. Yoo, S. W. Oh, J. Y. Kim, H. G. Kim, Y. J. Lee, S. Y. Youn, S.-H. Hong, and S.-J. Ko, "Deep learning for end-to-end kidney cancer diagnosis on multi-phase abdominal computed tomography," *NPJ Precis. Oncol.*, vol. 5, no. 1, p. 54, Jun. 2021, doi: 10.1038/s41698-021-00195-y.

[19] M. Wagih, F. E. Z. Abou-Chadi, H. El-Din, and N. Mekky, "Classification of ultrasound kidney images using PCA and neural networks," *Int. J. Adv. Comput. Sci. Appl.*, vol. 6, no. 4, 2015.

[20] M. Islam. (2021). CT Kidney Dataset: Normal-Cyst-Tumor and Stone. [Online]. Available: <https://www.kaggle.com/nazmul0087/ct-kidney-dataset-normal-cyst-tumor-and-stone>

BIOGRAPHIES OF AUTHORS



Ainagadda

Sriramy is currently a (M.Tech) student at Bonam Venkata Chalamayya Engineering College, pursuing a degree in Computer Science and Engineering .She completed her B.Tech in Computer Science and Engineering from the same institution in 2024. She is passionate about Machine Learning, Deep Learning, Artificial Intelligence, Big Data Analytics. She is proficient in Python, Java, and SQL, and has completed the Python for Data Science certification from NPTEL. She has also completed a 10-week AWS Cloud Internship through Eduskills. Her current research work focuses on kidney abnormalities detection using the YOLOv8 model integrated with the Flask framework. For any queries, she can be contacted at

Email: ramyaainagadda1@gmail.com



Mrs.Ganga Bhavani Billa

is Research Scholar at college, Koneru Lakshmaiah Education Foundation (KLEF) Green Fields, Vaddeswaram also Mrs.Ganga Bhavani is Associate Professor at college Bonam Venkata Chalamayya Engineering College, Odalarevu. She holds a M.Tech degree in Computer Science and Engineering in GIET College. Her Research areas are Machine Learning, Deep Learning and Artificial Intelligence. She has number of patents related to machine learning field and industrial designs on her innovative ideas and has been awarded with international patents and published different articles in international conferences.

She can be contacted at address:

Mrs.Ganga Bhavani Billa is Research Scholar at college, Koneru Lakshmaiah Education Foundation (KLEF) Green Fields, Vaddeswaram, A.P. -522302

Email: bhavanicse10@gmail.com

ORCID: <https://orcid.org/0000-0003-1433-5832>