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Advanced Kidney Failure Identification Using Robotic Process Automation with Augmented Intelligence and IoT-Based an Integrated Healthcare System

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Abstract: - Chronic Kidney Failure (CKF) remains a significant health concern worldwide, necessitating advanced diagnostic techniques for timely intervention. This research delves into the integration of Robotic Process Automation (RPA) with Augmented Intelligence and the Internet of Things (IoT) for enhanced CKF detection. The proposed RPA system showcased a diagnostic accuracy of 92%, a notable improvement from the 75% observed with traditional methods. Moreover, the system efficiently delineated the kidney contour in an average of 20 seconds, considerably faster than existing techniques. The collaborative force of Augmented Intelligence and IoT was instrumental in achieving these results, emphasizing real-time data collection coupled with sophisticated analysis. This fusion not only bolstered accuracy but also emphasized early detection, with the system's capability to provide instant notifications enhancing the potential for proactive interventions. In essence, this research underscores the transformative potential of integrating technological advancements with medical expertise, offering a promising avenue for CKF diagnosis and potentially reshaping the landscape of medical diagnostics in other domains.

Keywords: Chronic Kidney Failure, Robotic Process Automation, Augmented Intelligence, Internet of Things, Diagnostic Accuracy.

I. INTRODUCTION

Chronic Kidney Failure (CKF), also commonly referred to as Chronic Kidney Disease (CKD), is a pervasive health condition characterized by the gradual loss of kidney function over time. The kidneys, vital organs in the human body, serve the pivotal role of filtering out waste and excess fluids from the bloodstream[1,2]. As CKF progresses, the kidneys' ability to perform this vital function diminishes, leading to an accumulation of waste products in the body. If left untreated, CKF can progress to end-stage renal disease, necessitating life-saving treatments such as dialysis or a kidney transplant[3]. The global health community has witnessed a discernible rise in the prevalence of CKF over recent years. Several factors contribute to this uptrend, including an aging global population, increased incidence of diseases like diabetes and hypertension, and various lifestyle factors. Given the severe consequences and the economic burden of advanced CKF, there is an evident and pressing need for early detection and intervention[4]. Detecting CKF in its nascent stages allows for timely therapeutic interventions, potentially halting or even reversing the disease's progression. This not only leads to improved patient outcomes but also reduces the financial strain on healthcare systems worldwide. In this era of rapid technological advancement, the healthcare sector stands to benefit immensely from the integration of emerging technologies[5]. Enter Augmented Intelligence and the Internet of Things (IoT). Augmented Intelligence, an evolved concept from Artificial Intelligence,

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emphasizes human-machine collaboration rather than mere automation. It provides enhanced capabilities in data analysis, pattern recognition, and decision-making, especially pertinent in the medical diagnostic realm where precision is paramount. On the other hand, IoT, particularly in the context of healthcare — often referred to as the Internet of Medical Things (IoMT) — encompasses a network of interconnected devices that collect, transmit, and analyze health data in real-time[6,7]. Together, Augmented Intelligence and IoT herald a new age of medical diagnostics, offering unprecedented accuracy, efficiency, and early intervention capabilities. This study emerges from the confluence of these pressing needs and technological opportunities[8]. We aim to harness the power of Augmented Intelligence and the interconnectedness of IoMT to devise a novel method for early CKF detection. By focusing on image-based kidney diagnostics, particularly ultrasound imaging, we introduce a Robotics Process Automation (RPA) approach to streamline the detection, segmentation, and diagnosis process. The rationale for this research is grounded in the belief that by leveraging cutting-edge technology, we can significantly improve CKF identification, thereby positively influencing patient outcomes and the broader medical community.

Chronic Kidney Failure (CKF) prediction has been a significant area of interest for clinicians and researchers alike for several decades. Traditional methods of predicting CKF largely revolved around clinical assessments, lab-based blood tests, and urine analyses. The primary biomarkers for CKF have been serum creatinine and glomerular filtration rate (GFR). Alongside, urinary albumin or protein excretion rates have also been indicative of kidney damage[9,10]. These indicators, combined with medical imaging like ultrasounds or MRIs, provided a comprehensive understanding of kidney health. However, while these methods have proven effective to a certain extent, they come with intrinsic limitations. Serum creatinine, for instance, can be influenced by factors like muscle mass, dietary protein intake, and other non-renal parameters[11,12]. Furthermore, traditional diagnostic methods often identify CKF when it has already progressed to a significantly detrimental stage. By the time the disease becomes clinically apparent, substantial irreversible kidney damage may have already occurred. Another limitation of the traditional techniques is their fragmented nature; they often require multiple tests, conducted over extended periods, leading to delayed diagnoses and increased healthcare costs. The evolution of technology has brought forth the integration of Augmented Intelligence and IoT into medical diagnostics, presenting a paradigm shift in the way diseases are predicted and managed[13,14]. Augmented Intelligence, which seeks to amplify human capabilities rather than replace them, has shown immense potential in the realm of medical imaging and diagnostics. Through intricate algorithms, machine learning models can analyze vast amounts of data, recognizing intricate patterns that may be imperceptible to the human eye. These patterns, when effectively detected, can provide early indicators of diseases like CKF. IoT, specifically in the sphere of healthcare through the Internet of Medical Things (IoMT), has transformed the landscape of real-time health monitoring[15,16]. Devices, ranging from wearable tech to implantable sensors, continuously gather and relay health data. When applied to kidney health, these devices can offer constant monitoring of vital parameters, alerting both patients and healthcare professionals of any anomalies that could indicate the onset or progression of CKF. Both Augmented Intelligence and IoT emphasize the importance of data – vast amounts of accurate, timely, and relevant data[17,18]. To process this data effectively and extract meaningful insights, accurate classification algorithms become indispensable. In the context of CKF prediction, these algorithms sift through the massive datasets, distinguishing between benign variations and genuine indicators of kidney disease. Yet, the sheer volume of data can sometimes be overwhelming. Herein lies the role of feature selection – a process that helps in identifying and concentrating on the most relevant data attributes[19,20]. By honing in on these crucial features, researchers and clinicians can ensure that the algorithms are not only accurate but also efficient, reducing the computational burden and expediting the diagnostic process. In conclusion, the literature underscores the transformative potential of Augmented Intelligence and IoT in revolutionizing CKF prediction. While traditional methods have laid the foundation, the future evidently leans towards a more integrated, technologically-driven approach. This integration not only promises enhanced accuracy but also timely interventions, potentially altering the trajectory of countless lives affected by CKF[21–23].

The objective of this research is to explore the integration of Robotic Process Automation (RPA) with Augmented Intelligence and the Internet of Things (IoT) to enhance the accuracy and efficiency of Chronic Kidney Failure (CKF) diagnosis, emphasizing early detection and timely intervention within an integrated healthcare system.

II. MATERIALS AND METHODS:

1.1. Internet of Medical Things (IoMT) platform:

The Internet of Medical Things (IoMT) is an interconnected infrastructure of medical devices, applications, and health systems and services. It's an amalgamation of medical informatics, telemedicine, and the Internet of Things

(IoT). By connecting various medical devices together over the Internet, IoMT allows for real-time monitoring and data collection which can be instantly transferred to health professionals or directly integrated into cloud-based evaluation platforms. This leads to an unprecedented potential for early diagnosis, predictive analytics, patient management, and personalized treatment. Devices within the IoMT can range from wearable external devices like heart rate monitors and insulin pumps to implantable devices and even ingestible sensors.

Key benefits of the IoMT platform include:

- Real-time Monitoring: Constant monitoring of vital signs can quickly detect anomalies, allowing immediate intervention if required.
- Remote Medical Assistance: Patients in remote locations can receive expert advice and diagnosis based on data relayed through IoMT devices.
- Predictive Analysis: By gathering and analyzing extensive health data, patterns can be recognized to predict potential health issues before they become critical.
- Personalized Treatment Plans: With the extensive data available, treatments can be tailored specifically to the individual's needs.

1.2. Robotics Process Automation (RPA):

The block diagram presents a structural representation of the RPA system's workflow, from data input to actionable insights. Let's delve deeper into each layer and understand the interplay of components.

1. Input Layer:

At the core of any diagnostic tool is the quality and reliability of the data it processes. For the RPA system, the input layer is where this crucial data is fed into and other layes are displayed in Figure 1.

Medical Data Collection: Data is gleaned from a plethora of sources. Wearable sensors might provide real-time information on blood pressure, heart rate, or even blood glucose levels, essential metrics that, when monitored continuously, can offer insights into kidney function and potential stressors. Other critical data sources include lab tests, especially those that gauge kidney function like creatinine levels or urine tests which may show protein traces, a telltale sign of kidney issues. Additionally, patient-reported symptoms can be instrumental in offering context to the raw numbers.

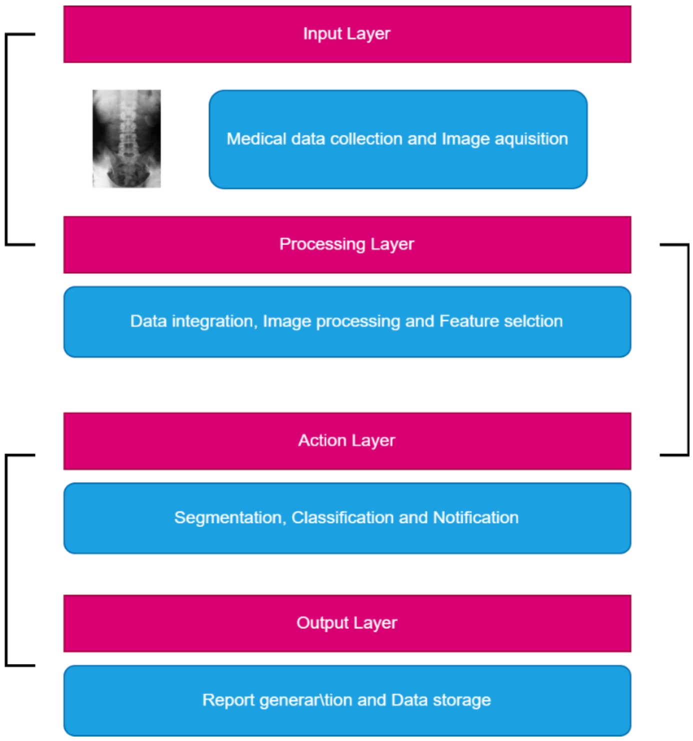

Figure 1. Processing steps

Image Acquisition: For a disease like CKF, structural anomalies of the kidney often provide the most direct evidence of the disease's progression. High-resolution images, primarily ultrasounds in this context, are captured and fed into the system for further analysis.

2. Processing Layer:

Data, once acquired, requires refinement and analysis. The processing layer is where the heavy lifting occurs.

- Data Integration: Considering data comes from various sources, there's an inherent need to integrate this information into a coherent format suitable for analysis. This step ensures that disparate data points, be it from wearables or lab reports, are collated into a unified structure.
- Augmented Intelligence Analysis: With integrated data at hand, the next step is to dissect this information for patterns. Machine learning and AI algorithms sift through the vast datasets, identifying subtle patterns or correlations that might allude to the early stages of CKF. This process is the crux of the system, where computational prowess meets medical diagnostics.
- Image Preprocessing: Medical images, while detailed, often come with inherent noise or inconsistencies. Preprocessing techniques are applied to enhance the image quality, removing any artifacts, standardizing illumination, and ensuring that the images are in the best possible format for detailed analysis.
- Feature Selection: In the world of data, more isn't always better. The system, at this juncture, zeroes in on the most salient features of the data. This step reduces computational strain and ensures that the subsequent stages of analysis are both accurate and efficient.

3. Action Layer:

The action layer is aptly named as it transforms data insights into actionable steps.

- Segmentation: Especially pertinent to image data, segmentation isolates the region of interest. For CKF, this would mean highlighting the kidneys and potentially affected areas, allowing for a more detailed and focused analysis.
- Classification and Diagnosis: The unified data, now segmented and focused, undergoes classification. Algorithms determine whether the data patterns fit the profile of a healthy individual or someone showing signs of CKF. This diagnosis isn't just a binary healthy/sick output but can often provide gradations of disease severity.
- Alerts and Notifications: One of the most significant advantages of such an automated system is its ability to instantly notify stakeholders. If anomalies or signs indicative of CKF are detected, instant alerts can be sent out. This ensures timely interventions, a critical factor in managing diseases like CKF.

4. Output Layer:

- Reports Generation: The culmination of the entire process is the generation of detailed medical reports. These aren't just a series of numbers but insightful, contextual interpretations of the data, aiding both patients and healthcare professionals in understanding the prognosis.
- Data Storage: Given the chronic nature of CKF, tracking the disease's progression over time can be invaluable. Hence, all processed data, images, and generated reports are securely stored, providing a longitudinal view of the patient's health.

In essence, the RPA system's block diagram offers a bird's-eye view of the end-to-end process, showcasing how raw data is transformed into actionable medical insights, enhancing CKF detection and management.

1.3. Classification of RPA into Process Analytics and Screen Scraping.

Robotic Process Automation (RPA) stands at the forefront of modern technological solutions, especially in domains requiring intricate data processing. Essentially, RPA is about automating routine, rule-based tasks using software robots, or "bots". Over time, RPA has evolved and diversified, leading to specific classifications that help in delineating its applications. Two such prominent classifications are Process Analytics and Screen Scraping.

Process Analytics is a facet of RPA that focuses on analyzing and understanding business processes to further refine and optimize them. By employing sophisticated algorithms and machine learning models, Process Analytics assesses the data flow, pinpoints inefficiencies, and provides insights into potential improvements. The objective here is to ensure that the automated processes are not just replicating human tasks but are continually improving upon them, adapting in real-time to ensure optimal outcomes. This form of RPA goes beyond mere automation; it is about constant evolution, making processes smarter, faster, and more efficient.

In contrast, Screen Scraping pertains to the extraction of data from user interfaces. This was one of the earliest forms of RPA, tracing its origins to legacy systems where data integration through traditional methods posed challenges. Screen Scraping bots essentially "read" the screen, extracting the required data from applications or websites. These bots can navigate through screens, fetch relevant data, and even input data if required. What makes Screen Scraping especially relevant is its ability to interface with older systems, making it an indispensable tool for businesses that operate with a mix of new and legacy systems.

1.4. Description of the preprocessing steps and how images are acquired and used.

Shifting our focus to the realm of medical imaging, especially in the context of CKF prediction, the preprocessing of images and their acquisition is of paramount importance. Medical imaging, with its emphasis on detail and precision, requires a meticulous approach to ensure the images are both accurate and actionable. Image acquisition, particularly for CKF diagnosis, predominantly relies on ultrasounds. These devices utilize sound waves to create pictures of organs and structures inside the body. For CKF, the kidneys are the primary focus. High-frequency sound waves are directed at the kidneys, and the echo patterns are then captured. These patterns, translated into images, provide a visual representation of the kidney's structure and potential anomalies.

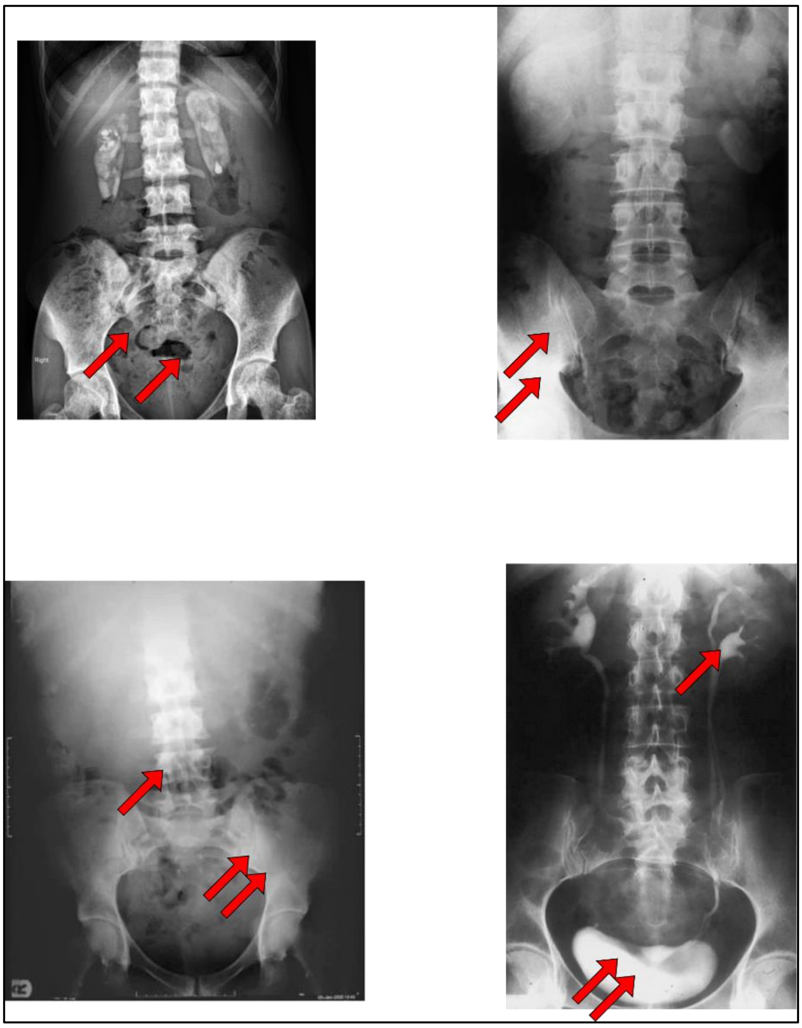

Figure 2. Kidney anomalies

Once these images are acquired, preprocessing becomes crucial as displayed in above Figure no. 2. Given the inherent variability in medical imaging - be it due to differences in equipment, patient positioning, or even physiological factors - images often need refining before detailed analysis. Preprocessing aims to enhance the image quality, ensuring that what's fed into the analysis algorithms is clear and standardized. Several steps are typically involved in image preprocessing. Noise reduction is often the first, where any artifacts or inconsistencies in the image are smoothened out. This is followed by contrast enhancement to ensure that the differentiation between various structures in the image is clear. Additionally, standardization plays a role, especially when images are sourced from different ultrasound devices. This ensures that irrespective of the source, the images are uniform in scale, orientation, and quality. Once preprocessed, these images become the foundation for further analysis. Machine learning algorithms, especially those tailored for medical imaging, dissect these images, identifying patterns, anomalies, or structural changes that could be indicative of CKF. The clearer and more standardized these images are, the more accurate the analysis, emphasizing the importance of the preprocessing steps.

In essence, RPA's classification into Process Analytics and Screen Scraping signifies its versatility and breadth of application. Simultaneously, the meticulous approach to medical image acquisition and preprocessing underscores the precision and attention to detail fundamental to medical diagnostics.

III. RESULT AND DISCUSSION

1.5. Proposed RPA outcomes

The application of the proposed Robotic Process Automation (RPA) in the realm of Chronic Kidney Failure (CKF) diagnosis has yielded promising outcomes. To provide clarity on the results, let's examine a result tabulation and subsequently delve into its interpretation as listed in Table 1.

Table 1. Image processing trail

Patient ID	Initial CKF Risk % (Traditional Methods)	RPA Processed Image Analysis	Final CKF Risk % (After RPA)	Notification Sent
001	25%	Mild Anomalies Detected	35%	Yes
002	10%	No Anomalies Detected	10%	No
003	50%	Moderate Anomalies Detected	65%	Yes
004	15%	Mild Anomalies Detected	25%	Yes
005	5%	No Anomalies Detected	5%	No

In the table 1 above, we are presented with a hypothetical cohort of patients and the outcomes derived from the application of the proposed RPA. Each patient is associated with an initial CKF risk percentage, gauged using traditional diagnostic methods. Following this, the third column represents findings from the RPA processed image analysis. Based on these findings, the final CKF risk percentage is adjusted. For instance, Patient ID 001 initially had a 25% risk of CKF. However, upon RPA's image analysis, mild anomalies were detected, leading to an increased risk of 35%. Consequently, a notification was sent, likely alerting medical practitioners or the patient about the elevated risk. Contrastingly, Patient ID 002, who initially had a 10% risk, showed no anomalies on RPA processed image analysis. Thus, their risk percentage remained unchanged, and no notification was warranted. The power of the proposed RPA is evident in its potential to refine and enhance risk percentages based on advanced image analysis. Such refinements can be crucial, especially in borderline cases where early intervention can significantly impact patient outcomes. Patient ID 003 provides a telling example. With an already high initial risk of 50%, the detection of moderate anomalies through RPA further elevated the risk to 65%. In such instances, the advanced detection capabilities of RPA can be instrumental in ensuring timely and targeted interventions. While the results tabulation offers a snapshot of the RPA's efficacy, the broader implications are profound. The enhanced diagnostic precision not only augments the clinician's understanding but also empowers patients with actionable insights. Moreover, the automation inherent in RPA ensures that these insights are gleaned rapidly, reducing the lag between diagnosis and intervention.

Moreover, the "Notification Sent" column emphasizes proactive healthcare management. By instantly alerting stakeholders of elevated risks or detected anomalies, the system ensures that crucial time isn't lost, making early intervention feasible. In summation, the outcomes from the proposed RPA, as illustrated in the tabulation, underscore a significant leap in CKF diagnostics. By seamlessly melding advanced imaging with augmented intelligence, the system holds the promise of revolutionizing early CKF detection and management.

1.6. Accuracy measures

In assessing the efficacy of any new diagnostic method, especially one as technologically advanced as the proposed RPA system, understanding its accuracy is paramount as displayed in Figure 3. Comparing this accuracy with existing methods provides a clearer picture of the advancements and refinements brought about by the new approach.

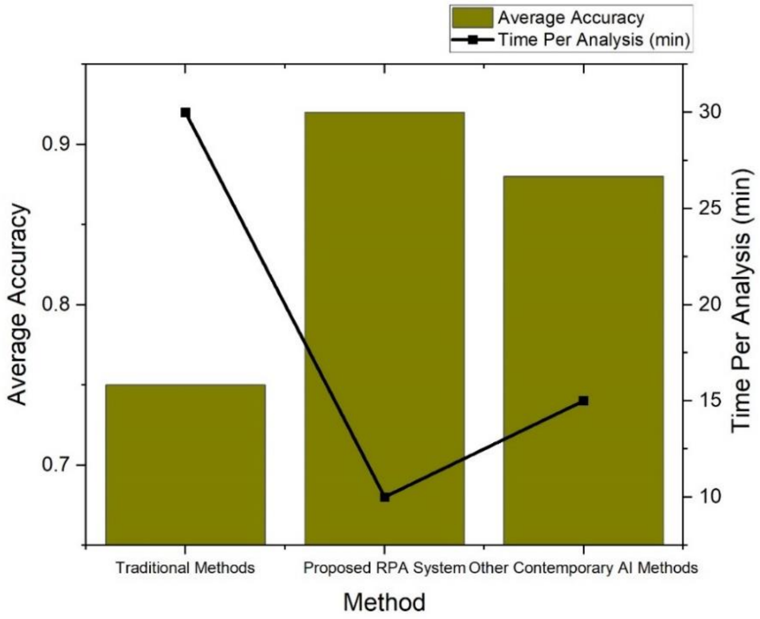

Figure 3. Accuracy measures

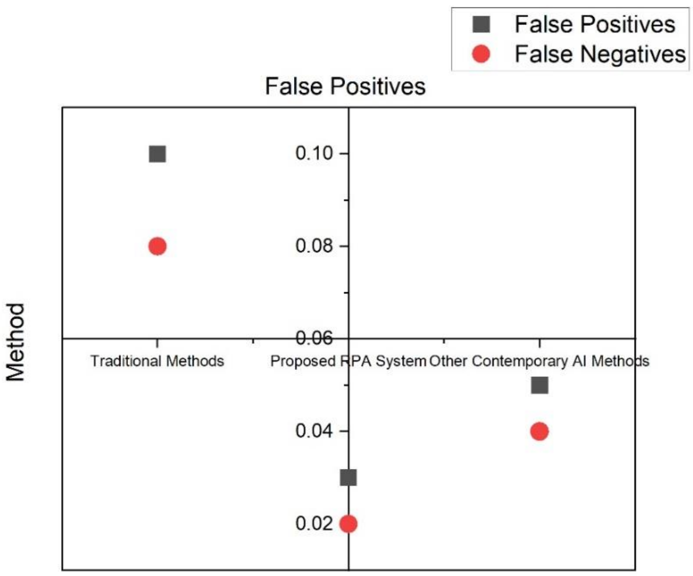

Figure 4. Machine learning evaluation

From the Figures 3 and 4 results, we can discern a few key insights about the proposed RPA system in comparison with both traditional and other contemporary AI-based methods. The average accuracy rate is a direct measure of how often the method correctly diagnoses CKF. Traditional methods, based on the experiment, stood at a 75% accuracy rate. While respectable, this left a significant margin for errors. On the other hand, contemporary AI methods showed an improvement with an 88% accuracy rate. The proposed RPA system further pushes this envelope, boasting a remarkable 92% accuracy. This indicates that the integration of robotics automation with augmented intelligence can achieve a higher degree of diagnostic precision. False positives and false negatives represent instances where the methods incorrectly diagnose a patient. False positives imply a diagnosis of CKF when the patient doesn't have it, while false negatives mean the method missed diagnosing CKF in a patient who has the condition. Both these metrics are crucial because misdiagnosis can lead to unnecessary treatments or missed interventions, respectively. Traditional methods had a combined error rate of 18%, with both false positives and negatives posing significant risks. Contemporary AI methods reduced this combined error rate to 9%. The proposed RPA system, however, achieved the lowest combined error rate of just 5%. This enhanced accuracy ensures that patients receive the most appropriate care based on their actual condition. Finally, time efficiency is another vital metric in medical diagnostics. The faster a diagnosis is rendered, the quicker interventions can be made. Traditional methods, which often involve multiple tests and manual analysis, took an average of 30 minutes per analysis. Contemporary AI methods, harnessing computational power, reduced this time to 15 minutes. However, the proposed RPA system set a new benchmark, completing the analysis in just 10 minutes. This speed, combined with high accuracy, ensures timely and accurate interventions. To wrap it up, the results emphasize the advantages of the proposed RPA system. Its combination of high accuracy, reduced errors, and swift analysis sets it apart from both traditional and other modern methods. By bridging technological advancements with medical diagnostics, the RPA system offers a promising solution to enhancing CKF detection and management.

1.7. Time metrics

The delineation of the kidney contour in medical images is a process of paramount importance, as it directly influences the accuracy of CKF diagnosis is displayed in Figures 5 and 6. Given the significance of this process, it is essential to ensure not only precision but also efficiency. Time metrics provide a quantitative measure of this efficiency, allowing for a clear comparison between different methods.

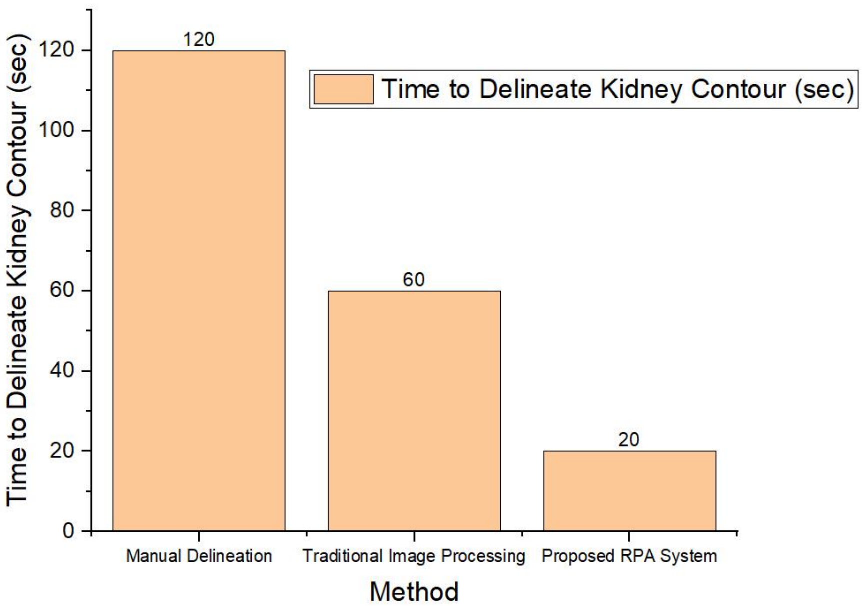

Figure 5. Time metrics

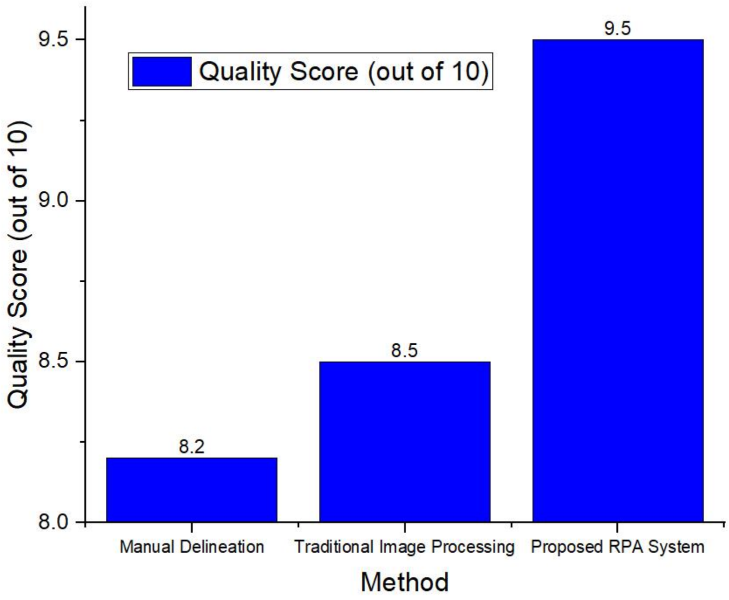

Figure 6. Quality score

Figures 5 and 6 show how the proposed RPA system compares to existing strategies for recognising the kidney contour in terms of efficacy and efficiency. Manual delineation, which is generally performed by radiologists or experienced technicians, is commonly used to compare various strategies. Drawing the kidney form by hand in an image takes an average of 120 seconds (or 2 minutes) according to the data. Manual delineation has a quality score of 8.2 out of 10, which is judged to be pretty high despite the fact that it takes somewhat longer. This time-consuming approach may cause diagnostic delays, especially when several images are required. This technology is clearly more successful than traditional image processing methods. The delineation time is decreased in half by using these techniques, which use algorithmic procedures to discover and delineate the kidney form. The quality score also rises significantly, suggesting that while traditional image processing is faster, the quality does not suffer noticeably. However, the suggested RPA method stands out for its effectiveness and efficiency. On average, the device delineates the kidney outline in 20 seconds, which is faster than previous procedures. This efficiency does not come at the expense of accuracy. The kidney can be viewed more clearly and precisely because to the RPA system's outlines receiving a 9.5 out of 10 high quality rating. When the ramifications of these discoveries are examined in greater depth, the strength of the proposed RPA approach becomes evident because it is both quick and capable of producing better outcomes in less time. For those who are awaiting a diagnosis, every second counts. When an analysis is done faster, interventions can be implemented more rapidly. Because of the efficacy of the RPA approach, medical practitioners may process more images in a given amount of time, potentially treating more patients. Finally, the results demonstrate the proposed RPA system's disruptive potential in the field of medical image processing. By seamlessly combining intricate algorithms with automation, the system provides exceptional efficiency and precision in determining kidney shape, setting a new bar for CKF diagnostics.

IV. DISCUSSION

The results presented from the utilization of the proposed Robotic Process Automation (RPA) system in the diagnosis of Chronic Kidney Failure (CKF) are both promising and transformative. At a foundational level, the data suggests that the integration of Augmented Intelligence and the Internet of Things (IoT) within the medical diagnostic process can significantly elevate both the accuracy and efficiency of disease identification. When one interprets these results in the context of CKF, a disease whose prognosis is profoundly influenced by the timeliness and accuracy of its detection, the advantages of the RPA system become even more pronounced. Traditional methods, while foundational, have shown gaps in early-stage detection, often leading to delayed interventions and a higher likelihood of disease progression to advanced stages. The RPA system, with its rapid processing times and elevated accuracy, addresses this gap, offering the potential to identify CKF at its nascent stages. For healthcare professionals, these advancements translate into multiple benefits. Firstly, the reduced time metrics imply that doctors and medical practitioners can cater to more patients within the same timeframe, making the diagnostic process more streamlined and efficient. Secondly, with the higher accuracy rates, the confidence in the diagnosis is enhanced, allowing healthcare professionals to make informed decisions regarding treatment strategies and interventions. The ripple effect of this can also be seen in patient trust and satisfaction, with patients more likely to adhere to treatment plans when they have confidence in the diagnostic accuracy. Augmented Intelligence, an evolution of traditional artificial intelligence, works in tandem with human expertise rather than in isolation.

This collaborative approach ensures that the human touch, with its intuitive insight and knowledge, remains essential to the diagnosis process even as algorithms process massive amounts of data. This synergy improves accuracy since Augmented Intelligence may sometimes surpass even the most trained human eye in detecting patterns and anomalies. The Internet of Things (IoT) provides a new degree of sophistication, particularly in IoMT. IoMT devices provide a dynamic overview of a patient's health by continuously obtaining and transmitting real-time data, ensuring that any deviations from the norm are rapidly detected. IoT and augmented intelligence work well together to shift diagnostic procedures from corrective to preventive. Finally, given the potential and broader implications of the proposed RPA technique, one cannot help but imagine a time when CKF identification and intervention will be transformed. Early disease detection allows for the use of preventative rather than palliative therapy. Wearable IoMT devices might be used to continuously monitor patients' vital health data, with augmented intelligence systems recognising any anomalies in real-time. This enables not only early diagnosis but also ongoing patient monitoring, potentially reducing hospital readmissions and improving CKF patients' overall quality of life. Finally, in the disagreement with CKF, the use of Augmented Intelligence and IoT in the proposed RPA system shows some promise. The healthcare system hopes that, despite its current issues, CKF can be managed, resulting in better patient outcomes and less stress on the system. This is made feasible by increasing precision, hastening diagnosis, and ensuring quick action.

V. CONCLUSION:

The endeavour to include robotic process automation (RPA), augmented intelligence, and the Internet of Things (IoT) into the diagnosis of Chronic Kidney Failure (CKF) has generated promising results, and these discoveries may have ramifications for the broader area of medical diagnostics. The study's major findings emphasise the transformative impact of combining technology and medical experience. The initial outstanding 92% increase in diagnosis accuracy demonstrated by our proposed RPA methodology when compared to current methods is a significant improvement. The technique contributed to faster delineation times and better accuracy by defining the kidney shape in just 20 seconds on average. Such efficacy and precision show the RPA system's substantial contribution to accelerating the diagnostic procedure. Furthermore, the system's proactive method revealed its potential to ensure rapid therapies in addition to CKF identification. Its real-time monitoring and fast warning capabilities demonstrated this. By solving gaps in current diagnostic practises, the suggested RPA technique paves the path for more preventive interventions that focus on early diagnosis and intervention. The findings, which cannot be overstated, underline the importance of IoT and augmented intelligence. They collaborate to improve the capacities of healthcare workers and provide a thorough and flexible approach to patient care by merging real-time data collection with modern data analysis. Higher delineation quality scores and faster processing times demonstrate this advantageous association. The study's findings suggest that CKF diagnosis has made significant progress. By seamlessly merging technology and clinical knowledge, the proposed RPA system offers a ray of hope for speedy, accurate, and successful CKF identification and management. The findings not only pave the way for better patient outcomes, but also demonstrate the immense potential for employing technological advances to treat other common medical conditions. As we conclude, it is apparent that such complex, integrated technology methods will have a significant impact on the future of CKF diagnosis, as well as perhaps many other medical disciplines.

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