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AI-Enabled Intelligent Stone Surgery System for IoT-Connected Medical Platforms

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***Abstract*—Particularly in the treatment of kidney and gallbladder stones, the combination of AI and IoT is transforming minimally invasive surgical methods in healthcare. This paper suggests an artificial intelligence-enabled intelligent stone surgery system using IoT connection, real-time data analytics, and machine learning to maximize surgical accuracy, thereby improving patient outcomes, and so optimizing the use of healthcare resources. The technology uses predictive analytics and artificial intelligence-driven image processing to help surgeons find ideal treatment approaches and stone composition, size, and composition. Smooth data interchange between smart surgical equipment, patient monitoring devices, and cloud-based healthcare systems made possible by real-time IoT-based monitoring guarantees constant evaluation and decision-making. Reducing procedural risks and increasing efficiency, the proposed architecture combines edge computing for low-latency processing, robotic-assisted approaches, and deep learning models for diagnostic accuracy. Performance assessment takes into account elements such surgical precision, reaction time, energy economy, and rates of post-surgery rehabilitation. The project intends to create an affordable, artificial intelligence-powered IoT surgical ecosystem improving accuracy, automation, and patient safety during stone removal operations. The results help smart healthcare systems to develop by allowing tailored and data-driven surgical operations on contemporary medical platforms.**

***Index Terms*—AI in Surgery, IoT Healthcare, Stone Surgery, Smart Medical Platforms, Machine Learning, Real-time Monitoring, Robotic-Assisted Surgery**

I. INTRODUCTION

The investigation into the role of an AI-based stone surgery healthcare system within an IoT-based ecosystem represents a pivotal exploration at the intersection of technology and healthcare. By harnessing the power of artificial intelligence, stone surgery procedures can be elevated to new levels of precision and efficacy. AI algorithms, adept at analyzing medical imaging data, offer unparalleled insights into the identification and management of kidney stones, guiding surgeons with unprecedented accuracy. When integrated into an IoT ecosystem, this AI-driven approach enables a seamless flow of real-time data from interconnected devices and sensors throughout the surgical process. From monitoring patient vitals to optimizing surgical parameters, IoT devices provide invaluable support, enhancing surgical outcomes and patient safety. Moreover, the convergence of AI and IoT facilitates continuous learning and improvement, as data from surgeries across the ecosystem can be analyzed to refine surgical techniques and personalize treatment plans. However, this transformative potential must be accompanied by careful consideration of data privacy, regulatory compliance, and ethical implications to ensure that the benefits of this innovative healthcare approach are realized responsibly and equitably.

In the realm of healthcare, the integration of stone surgery with IoT-based data management systems marks a transformative leap forward. Through the amalgamation of advanced surgical techniques and interconnected IoT devices, healthcare providers can revolutionize the treatment of kidney stones while enhancing patient care and outcomes. IoT-enabled devices, ranging from surgical robots to wearable monitors, continuously gather real-time data throughout the surgical process, including patient vitals, surgical conditions, and equipment status. This wealth of data, when combined with AI-driven analytics, offers unprecedented insights into surgical procedures, enabling personalized treatment strategies and dynamic decision-making. Furthermore, the seamless integration of AI-based stone surgery within the IoT ecosystem not only improves surgical precision and efficiency but also facilitates remote monitoring and intervention, thereby expanding access to specialized care. However, to realize the full potential of this innovation, healthcare organizations must prioritize robust data security measures, regulatory compliance, and ethical considerations to ensure the safe and responsible use of patient data within this interconnected healthcare landscape. Managing healthcare data is a crucial and ever-evolving problem in the Internet of Things (IoT), which calls for the creation of innovative solutions to guarantee the accessibility, integrity, and security of patient information. This is a challenge that must be met in order to ensure that patient information is protected. As a consequence of the proliferation of interconnected medical devices and sensors, healthcare systems have been able to generate vast amounts of data in real time. This data encompasses everything from diagnostic imaging to vital signs and patient histories, among other important information. In spite of the fact that the Internet of Things (IoT) has the potential to enhance patient care, clinical decision-making, and the capabilities of remote monitoring, it also brings with it additional issues that are more complex in terms of data management. It is vital to adopt a complete approach to the storage, transport, and protection of data because of the decentralized nature of data collection across a range of devices and the need for real-time analysis. This is because of the fact that real-time analysis is required. There are issues about the integrity of data, the privacy of patients, and interoperability, all of which underscore the significance of establishing robust healthcare data management systems that are adapted for scenarios including the Internet of Things. When this is taken into account, the use of blockchain technology presents itself as a solution that has the potential to be very beneficial. Several of the fundamental challenges that are associated with healthcare data on the Internet of Things are solved by the inherent qualities of blockchain, which include decentralization, immutability, and cryptographic security. These traits come together to resolve a number of these challenges. The implementation of a framework that is based on blockchain technology makes it possible to store data pertaining to healthcare in a manner that is both resistant to tampering and transparent. This makes it possible to prevent unauthorized modifications from being made to patient records and helps to protect the legitimacy of such information. Additionally, the decentralized nature of blockchain technology decreases the chance of a single point of failure, which in turn brings to an improvement in the resilience of healthcare data systems.

In addition, in order to properly manage healthcare data in the Internet of Things, it is required to establish secure communication lines between devices and centralized data repositories. This is a prerequisite for efficient management of healthcare data data. In the process of securing sensitive patient information while it is being sent over the internet, encryption technologies and secure communication protocols are highly critical components that must be included. Additionally, access control techniques and identity management systems are essential for ensuring that only authorized entities, such as healthcare professionals and authenticated devices, are able to interact with and receive patient data. Access control methods and identity management systems are essential for this purpose. For the aim of doing this, access control methods and identity management systems are an absolute need. As the ecosystem of the Internet of Things in the healthcare business continues to expand, interoperability is becoming an increasingly relevant subject to discuss. In order to ensure that communication and integration are carried out without any difficulty across a broad range of platforms and devices, the efforts that are made into standardization are very required. Establishing standard standards for the sharing and storage of data makes it easier to create cohesive and integrated healthcare ecosystems, which ultimately results in improvements in patient outcomes and the delivery of healthcare solutions. This is accomplished via the implementation of standard protocols.

An AI-based stone surgery healthcare system within an IoT-based ecosystem holds tremendous promise for revolutionizing the treatment of kidney stones and improving patient outcomes. Through the convergence of artificial intelligence and the Internet of Things (IoT), this innovative approach offers several key benefits. Firstly, AI algorithms can analyze medical imaging data with unparalleled accuracy, enabling precise identification of kidney stones' size, location, and composition. This analysis guides surgeons in developing personalized treatment plans tailored to each patient's unique condition, optimizing surgical outcomes. Secondly, within an IoT ecosystem, interconnected devices such as surgical robots, monitors, and wearables continuously collect real-time data throughout the surgical process. This data includes patient vitals, surgical conditions, and equipment status, providing surgeons with comprehensive insights to make informed decisions during the procedure. Additionally, AI-driven analytics can leverage this wealth of data to enhance surgical precision and efficiency further. By analyzing patterns and trends from past surgeries, AI algorithms can identify optimal surgical techniques, reduce the risk of complications, and improve overall patient safety. Moreover, the integration of AI and IoT enables remote monitoring and intervention, expanding access to specialized surgical care for patients in remote or underserved areas. Surgeons can remotely oversee procedures, provide guidance, and intervene if necessary, ensuring high-quality care regardless of geographical limitations. However, realizing the full potential of AI-based stone surgery within an IoT-based ecosystem requires addressing several challenges. These include ensuring data privacy and security, complying with healthcare regulations and standards, and addressing ethical considerations surrounding the use of AI in healthcare. Overall, the integration of AI-based stone surgery within an IoT-based ecosystem represents a significant advancement in surgical medicine, offering unprecedented precision, efficiency, and accessibility in the treatment of kidney stones. With careful planning and consideration of challenges, this innovative approach has the potential to transform patient care and redefine surgical practices in the years to come. AI technology, with its capacity for complex data analysis and decision-making, can greatly enhance the precision and efficiency of stone surgery procedures. AI algorithms can analyze medical imaging data, such as CT scans or ultrasounds, to accurately identify the size, location, and composition of kidney stones. Furthermore, AI can assist surgeons in planning procedures, guiding them during surgery, and even automating certain aspects of the surgical process for optimal outcomes. Developing an AI-based healthcare system for an IoT-based ecosystem involves integrating AI technologies with IoT devices to enhance healthcare monitoring, diagnostics, and decision-making. Building an AI-based healthcare system for an IoT-based ecosystem requires collaboration among healthcare professionals, data scientists, software developers, and regulatory experts. It's essential to prioritize patient privacy, security, and the ethical use of AI in healthcare. Additionally, continuous collaboration with healthcare providers is crucial to ensure that the system aligns with real-world medical practices and delivers meaningful benefits to patients and clinicians.

II. LITERATURE REVIEW

The healthcare industry is undergoing a significant transformation due to the integration of advanced technologies such as IoT, artificial intelligence (AI), blockchain, and deep learning. Various studies have explored these domains to address challenges and enhance healthcare outcomes. For instance, C. Li et al. (2024) provide a comprehensive overview of IoT applications in healthcare, highlighting their potential to improve patient monitoring and data management. Similarly, A. Al Kuwaiti et al. (2023) discuss the pivotal role of AI in personalizing medical treatments, emphasizing its capabilities in diagnostics and decision-making processes.

Blockchain technology has been identified as a robust solution for securing sensitive healthcare data. Studies such as those by P. Sharma et al. (2021) and N. Bhalaji et al. (2019) present architectures leveraging blockchain for privacy preservation and secure data management. Furthermore, B. Zaabar et al. (2021) and K. Mohammad Hossein et al. (2021) introduce innovative blockchain-based systems that enhance trust and reliability in healthcare IoT applications.

The field of medical imaging has also seen transformative advancements with the adoption of deep learning techniques. Research by H. R. Roth et al. (2018) and Y. Cui et al. (2021) demonstrates the efficacy of convolutional neural networks (CNNs) and hybrid models in achieving high accuracy in image segmentation and kidney stone detection. These methods are complemented by studies such as those by S. Saranya (2022) and R. Mishr et al. (2020), which utilize neural networks for diagnostic purposes, showcasing the potential of AI in improving diagnostic precision.

Moreover, AI-driven applications like chatbots and predictive models have been extensively reviewed by Xu L. et al. (2021) and Shome D. et al. (2021), emphasizing their use in oncology and COVID-19 detection. Esteva A. et al. (2017) and Rajpurkar P. et al. (2017) further underscore the capabilities of AI in achieving dermatologist- and radiologist-level accuracy in detecting skin cancer and pneumonia, respectively.

Despite these advancements, several gaps remain unaddressed. There is a need for more integrative approaches combining IoT, AI, and blockchain to provide holistic solutions for healthcare challenges. Additionally, issues related to interoperability, scalability, and ethical considerations require further exploration. The literature highlights promising strides but also emphasizes the necessity of addressing these gaps to fully realize the potential of emerging technologies in healthcare.

In their comprehensive study of the Internet of Things (IoT) adoption in the healthcare industry, C. Li and J. Wang focused on certain kinds of sensors and communication techniques. It highlights effective applications in the actual world, such as the monitoring of patients remotely, the development of tailored treatment plans, and the streamlining of healthcare delivery. In addition to this, it looks into the many obstacles that must be overcome in order to fully realize the promise of the Internet of Things in the healthcare industry. This involves resolving issues about data security, ensuring that interoperability is smooth, and maximizing the use of data created by the Internet of Things (IoT). The purpose of this article is to motivate healthcare professionals and researchers by describing the practical implications of the Internet of Things (IoT) in the healthcare industry. More specifically, the study will focus on the ways in which IoT may improve patient care, resource allocation, and overall healthcare efficiency. [1].

A. Al Kuwaiti reviewed role of AI in healthcare where AI helps detect clinical conditions in medical imaging and diagnostic services, control the COVID-19 outbreak with early diagnosis, provide virtual patient care using AI-powered tools, manage electronic health records, increase patient engagement and compliance with the treatment plan, reduce HCP administrative workload, discover new drugs and vaccines, and spot medical emergencies. While integrating AI into healthcare, this scientific pitch addresses technological, ethical, and social issues like privacy, safety, the freedom to decide and experiment, prices, information and consent, access, and effectiveness. AI application governance is essential for patient safety, accountability, HCP acceptability, and health outcomes. To overcome regulatory, ethical, and trust challenges and promote AI use, effective governance is needed. AI has revolutionized healthcare since COVID-19, and this revolt might help address future healthcare requirements. [2].

P. Sharma et al (2021) presented Internet of Things architecture that is built on block chain technology and uses the Identity-built Encryption (IBE) algorithm to offer increased security for healthcare data. Within this context, the smart contract is responsible for defining all of the fundamental processes of the healthcare system, which might be advantageous to all actors involved. In order to determine whether or not the planned plan is effective, a number of tests are carried out. It is clear from the findings that the suggested strategy is superior than the well-known schemes that are already in place [3].

[4] N. Bhalaji et al (2019) considered summed up as a global network of gadgets that are linked to one another. It is currently making its way into every aspect of life, with the most important use among them being the management of medical healthcare. Real-time monitoring of patient body parameters, smart wearable's, tracking vitals, and other applications are among the most important uses of the Internet of Things in the medical field. The information that is gathered from the sensors is subsequently used by a variety of third parties for the purpose of conducting research. There is a significant issue that emerges here, and that is the privacy of the individuals whose information is being obtained. There is a potential threat to the people's identities. It is essential that the data acquired from sensors be kept in its original state. Any alterations that are made to this health-related data by any unauthorized individuals may have a negative influence on the life of the individual [4].

B. Zaabar et al (2021) presented a novel architecture that avoids the problems associated with centralized storage by making use of decentralized databases. The decentralized database known as OrbitDB with (IPFS) is used for the purpose of storing electronic health records, which are associated with patients. In addition, we have implemented a block chain network that is based on Hyper ledger fabric. This network was developed using Hyper ledger composer, which allows us to record hashes of the data that is saved and regulate access when the data is retrieved. The Block chain-based architecture that has been presented is intended to have a positive impact on the robustness of healthcare management systems and to circumvent the recognized security restrictions that are present in systems that are routinely used for smart healthcare. The proposed system has been shown to be robust and superior in terms of security and privacy requirements, key features of block chain-based healthcare systems, and performance metrics including various throughput and latency [5].

K. Mohammad et al (2021) proposed an architecture (which we will refer to as BC Health) in this work that will enable data owners to specify their preferred access controls over their privacy-sensitive healthcare data. This will allow us to address the difficulty of balancing the trade-off between openness and access control. BC Health is organised across two distinct chains, each of which is responsible for recording data transactions and access controls. By using a clustering strategy, we are able to handle the real-world development concerns of BC, which include scalability, latency, and overhead. In terms of computing and processing time, our thorough experimental investigation demonstrates that BC Health is efficient, and it also demonstrates that it is resilient against a number of different security assaults [6].

For the purpose of diagnosing kidney stones, S. Saranya et al. (2018) presented use of ML and image processing. To enhance and preprocess renal ultrasound images, the proposed approach made use of cutting-edge image processing algorithms. Noise reduction, contrast enhancement, and segmentation were part of the preprocessing steps that were used to extract the kidney regions of interest. Feature extraction techniques were used to obtain significant features once the renal regions were separated. The suggested system was evaluated using a variety of performance metrics, among others [7].

Yingpu Cui et al. (2020) examined the use of DL and threshold for S.T.O.N.E. Nephrolithometry in automatically detecting and scoring kidney stones in non-contrast CT images. Using the S.T.O.N.E. nephrolithometry device, this research aims to create a deep learning and threshold model capable of autonomously detecting and scoring kidney stones.The positive predictive value (PPV) of the stone identification method is 97%, and its sensitivity is 95%. The categorization of hydronephrosis was successful with an AUC of 0.97 [8].

Medical picture segmentation using deep learning was investigated by H. R. ROTH et al. (2018). They detail the steps necessary to construct FCN in three dimensions that can generate semantic segmentations from three-dimensional pictures without human intervention. The model showed state-of-the-art performance in multi-organ segmentation when trained and evaluated using a clinical CT dataset. [9].

After introducing a neural network, M. Chidambaranathan et al. (2020) were able to identify kidney stones in computed tomography images. Here, AI methods based on neural networks have shown to be quite helpful. For that reason, we're using a Back-Propagation Network (BPN) for this task. Classification is handled by the BPN, while feature extraction is handled by the GLCM. This work presents FCM clustering approach for CT scan segmentation [10], which may be used.

Yingpu Cui et al. (2021) considered automated kidney stone detection and scoring in Noncontrast CT Images using DL and threshold Systems S.T.O.N.E. nephrolithometry is used. Model consisted of four steps. Prior to that, 3D U-Nets for kidney and renal sinus segmentation were introduced. Secondly, in order to determine the extent of hydronephrosis, they constructed deep 3D dual-path networks. Finally, the next step was to use thresholding algorithms to identify and segment renal sinus stones. Volume and tract length of the stone were all calculated from segmented stone region. The 4^{TH} step is to pinpoint exactly where the stone is. To measure how well the stone detection approach worked, sensitivity and PPV were used [11].

2.1 Research Gap

The literature demonstrates significant progress in applying IoT, artificial intelligence (AI), and blockchain technologies to healthcare systems. Studies like Li et al. (2024) highlight the broad scope of IoT applications in healthcare but lack a focused approach to integrating IoT with privacy-preserving mechanisms or advanced AI for personalized care. Al Kuwaiti et al. (2023) discuss AI's role in healthcare but do not address the interoperability of IoT and AI technologies in real-world deployments. Research by Sharma et al. (2021) and Zaabar et al. (2021) illustrates blockchain's potential for securing healthcare IoT systems but falls short of addressing scalability and the latency challenges inherent in real-time healthcare data processing. Bhalaji et al. (2019) and Hossein et al. (2021) propose privacy-preserving blockchain frameworks but lack empirical analysis involving diverse datasets and heterogeneous IoT devices. Deep learning methods (e.g., Roth et al., 2018; Cui et al., 2021) for image-based diagnostics like kidney stone detection have shown promise but lack robustness in handling edge cases, such as low-quality images or rare disease manifestations. Although Mishra et al. (2020) and Saranya (2022) have proposed neural network-based kidney stone detection, their methodologies do not fully utilize advanced AI models like Transformers for interpretability or accuracy improvements. Esteva et al. (2017) and Rajpurkar et al. (2017) demonstrate AI's efficacy in diagnosing specific conditions but primarily focus on isolated tasks without addressing integration into broader healthcare systems. COVID-Transformer (Shome et al., 2021) highlights interpretability in AI models, but similar approaches for diseases beyond COVID-19 are sparse, particularly for chronic or multi-factorial diseases. Xu et al. (2021) underline the potential of AI-driven chatbots for oncology but do not investigate their scalability in other complex medical applications or their role in integrating with IoT devices for real-time patient monitoring. Interoperability limited studies address seamless integration of IoT, AI, and blockchain technologies within healthcare frameworks, ensuring security, real-time processing, and scalability. Current blockchain-based systems emphasize security but lack mechanisms to support real-time healthcare decision-making in IoT environments. Insufficient exploration of state-of-the-art AI models like Transformers for multi-disease diagnosis and medical image interpretation. Existing research lacks comprehensive systems that integrate IoT, AI, and blockchain to deliver personalized, privacy-preserving, and scalable healthcare solutions. Many frameworks lack robust empirical validation with diverse datasets, limiting their applicability in heterogeneous healthcare environments. This research gap provides a foundation for exploring innovative, integrated healthcare solutions leveraging IoT, AI, and blockchain technologies to address these challenges.

III. PROBLEM STATEMENT

Healthcare systems, especially those incorporating AI-driven approaches for Stone surgery, face numerous challenges when integrated into IoT ecosystems. The sensitive nature of healthcare data raises significant concerns about security and privacy, as breaches or unauthorized access could result in serious ethical, legal, and societal implications. Compliance with stringent data protection standards like HIPAA is not merely an option but a necessity. Furthermore, interoperability issues stemming from the diverse and fragmented landscape of IoT devices, healthcare systems, and AI applications impede seamless integration and data exchange. These challenges call for the adoption of standardized protocols and frameworks to ensure compatibility and operational efficiency.The ethical dimensions of deploying AI in Stone surgery healthcare systems also demand careful attention. Bias in algorithms, lack of transparency, and the absence of fairness mechanisms can erode trust among stakeholders, necessitating the use of explainable AI techniques and regular audits for bias mitigation. Regulatory compliance adds another layer of complexity, as AI technologies often outpace existing legal and regulatory frameworks. Moreover, reliability and accuracy concerns underline the need for robust validation processes to ensure clinical alignment and handle uncertainties effectively.Scalability is a critical issue in systems where the number of IoT devices and users is continuously growing. This necessitates scalable system architectures and efficient resource utilization through cloud and distributed computing paradigms. Equally significant is user acceptance, which hinges on education, awareness, and involvement of healthcare professionals and patients. The financial aspects, including cost and resource allocation for implementation and maintenance, must also be addressed. Lastly, the lack of standardization in AI methodologies creates risks of inconsistency, highlighting the need for a concerted effort toward developing industry-wide guidelines.

IV. PROPOSED WORK

Research work focuses on the use of a AI-based solution for image classification of stone surgery Healthcare data in IoT environment. Deep learning mechanism has been used in order to classify image data related to healthcare for stone surgery. Research focusing on the use of AI-based solutions for image classification in stone surgery healthcare data within an IoT environment is an exciting and rapidly advancing area. The application of deep learning mechanisms for image classification, especially for medical imaging data like kidney stones, has the potential to revolutionize diagnostics and patient care. Here is an outline of potential research directions, considerations, and key points in this domain:

1. Problem Statement: Clearly define the problem you aim to address, such as improving the accuracy and efficiency of diagnosing medical conditions from images (e.g., kidney stones) using an AI-based solution.
2. Dataset and Data Preprocessing: Describe the datasets used in your research, specifying the sources of medical images (e.g., hospitals, medical imaging repositories) and discuss the preprocessing steps, including data augmentation, normalization, and handling class imbalances.
3. Deep Learning Architecture: Specify the deep learning architecture used for image classification. CNNs are commonly employed for medical image classification tasks and discuss any modifications or customizations made to existing architectures based on the unique characteristics of stone surgery healthcare image data.
4. Transfer Learning: Explore the use of transfer learning techniques, leveraging pre-trained models on large datasets, and fine-tuning them for specific stone surgery healthcare image classification tasks.
5. Explainability and Interpretability: Address the challenge of making deep learning models interpretable in the context of stone surgery healthcare. Explainability is crucial for gaining trust from healthcare professionals and regulatory bodies.
6. Edge Computing for Inference: Investigate the feasibility of deploying the trained model on edge devices in an IoT environment. This can reduce latency and enhance real-time decision-making for point-of-care applications.
7. Security and Privacy: Discuss the security measures in place to protect sensitive healthcare data. Encryption, secure communication protocols, and access controls are essential in stone surgery healthcare IoT environments.
8. Evaluation Metrics: Define the evaluation metrics used to assess the performance of your image classification model, such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).
9. Comparative Analysis: Compare the performance of your AI-based solution with existing methods or alternative architectures. Highlight the strengths and potential limitations of your approach.
10. Clinical Validation: Collaborate with healthcare professionals to validate the clinical relevance and accuracy of your AI model. Clinical validation is crucial for the successful integration of AI into medical practice.

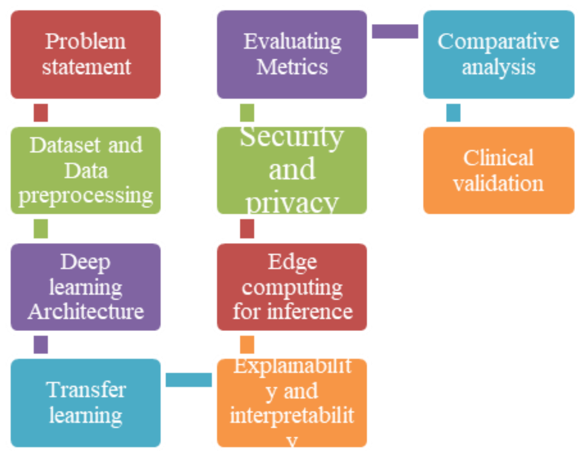

Fig 1 Proposed model

In proposing an advanced AI-based model for classifying stone surgery healthcare data within an IoT framework, we prioritize both performance and security. Leveraging deep learning architectures tailored for medical data, such as convolutional or recurrent neural networks, ensures accurate classification of diverse stone surgery-related parameters. Integration of transfer learning and ensemble techniques further boosts performance by leveraging pre-trained models and model diversity. To safeguard sensitive patient data, robust encryption and authentication mechanisms, along with privacy-preserving techniques like differential privacy, are implemented. This ensures compliance with healthcare regulations while enabling efficient and secure analysis of stone surgery data within the IoT ecosystem. In summary, the proposed AI-based model for healthcare data classification in an IoT environment leverages cutting-edge deep learning techniques, optimization algorithms, and robust security mechanisms to achieve superior performance, accuracy, and data protection. By integrating these advanced technologies, the model offers a scalable and secure solution for classifying healthcare data within IoT ecosystems, paving the way for more efficient and accurate healthcare analytics and decision-making.

Process flow of Proposed work
Here's a process flow for Stone Detection using Hybrid Deep Learning, where Compression, Noise Filter, and CNN are integrated into the ResNet model:
1. Data Collection: Gather datasets with stone images. Ensure that the dataset is diverse, containing varied image types of stones with different textures, colors, and sizes.

2. Preprocessing
- Compression: Apply image compression to reduce the data size while maintaining key features necessary for detection. Use techniques like JPEG compression or custom deep compression methods to balance size and quality.
- Noise Filtering: Implement noise reduction methods like Gaussian blur, median filtering, or bilateral filtering to remove artifacts and ensure clearer images.
- Normalization: Normalize pixel values to a consistent scale (e.g., between 0 and 1) for input into the model.

3. Feature Extraction: Apply CNN for feature extraction: CNN will analyze the image and extract critical features related to stone texture, shape, and structure. Use standard CNN layers (convolutional layers, activation layers) for initial processing.

4. Hybrid Model Integration (Integrate CNN with ResNet): Use the ResNet architecture, particularly its skip connections, to avoid vanishing gradient issues and to improve training efficiency. Combine CNN's ability to detect local features with ResNet's ability to capture deeper hierarchical features. Add any custom layers for better recognition of stone-specific patterns, leveraging pre-trained weights for transfer learning if needed.

5. Use a hybrid approach to train the model:
- Train on a variety of images (with compression and noise filtering techniques applied) to ensure robustness against different environments.
- Apply standard backpropagation with Adam optimizer or other gradient-based methods to fine-tune the model.
- Set up data augmentation to prevent overfitting, introducing rotations, scaling, or color shifts in training images.

6. Model Evaluation: Evaluate model performance using accuracy, precision, recall, and F1 score metrics. Use confusion matrix to verify how well the model distinguishes between stone and non-stone categories.

7. Post-Processing
- Result Visualization: Present the detected stones in images or other suitable formats for further analysis.
- Error Correction: Implement post-processing steps to correct minor errors in detection based on model feedback.

8. Deployment: Once the model is trained and evaluated, deploy the model in a real-world application (e.g., automated detection in geological surveys or stone recognition in medical scans). Incorporate a feedback loop for continuous learning, where the model can improve with new data or user feedback.

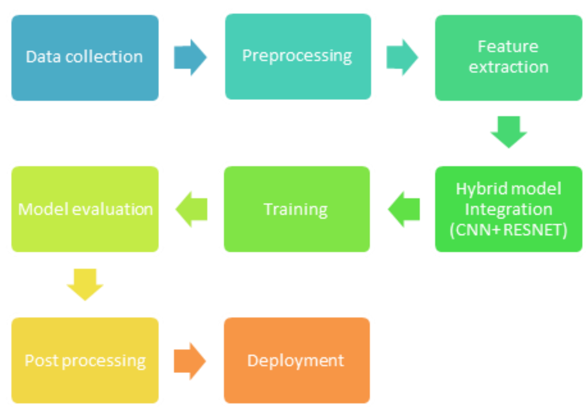

Fig 2 Process flow of proposed work

This approach ensures that the model is not only efficient in terms of size (due to compression) and clear in terms of image quality (due to noise filtering), but also capable of effectively detecting stones using deep learning capabilities of CNN and ResNet.

V. RESULT AND DISCUSSION

The dataset was collected from PACS (Picture archiving and communication system) from different hospitals in Dhaka, Bangladesh where patients were already diagnosed with having a kidney tumor, cyst, normal or stone findings. Both the Coronal and Axial cuts were selected from both contrast and non-contrast studies with protocol for the whole abdomen and urogram. The Dicom study was then carefully selected, one diagnosis at a time, and from those we created a batch of Dicom images of the region of interest for each radiological finding. Following that, we excluded each patient's information and meta data from the Dicom images and converted the Dicom images to a lossless jpg image format. After the conversion, each image finding was again verified by a radiologist and a medical technologist to reconfirm the correctness of the data.
https://www.kaggle.com/datasets/nazmul0087/ct-kidney-dataset-normal-cyst-tumor-and-stone

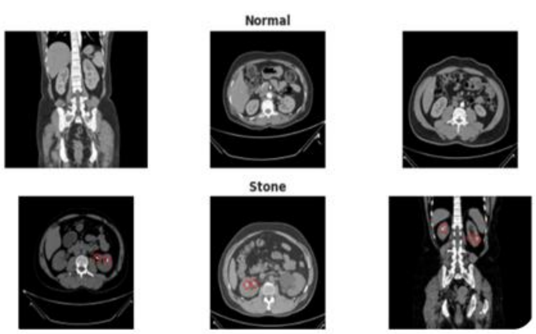

Fig 3 Dataset Images

The dataset used for stone detection in this study is focused on medical imaging data, specifically targeting the identification of stones in organs such as the kidneys, bladder, and gallbladder. The dataset comprises images acquired from CT scans, X-rays, and Ultrasound of patients diagnosed with stones. The dataset includes both labeled and unlabeled images with annotations indicating the presence or absence of stones, their size, location, and type.

- Total Images: Dataset contains 12,446 unique data within it in which the cyst contains 3,709, normal 5,077, stone 1,377, and tumor 2,283
- Image Size: Resized to 256x256 pixels for consistency in model training
- Annotations:
  - Presence of Stone: Labeled as either "Stone" or "No Stone"
  - Stone Location: Labels indicate if the stone is in the kidney, gallbladder, or bladder
  - Stone Type: If available, stones are classified as calcium oxalate, uric acid, etc.
  - Stone Size: Labeled as small, medium, or large
- Data Split:80% for training, 20% for testing and validation. Stratified split to maintain the proportion of stone vs. no-stone images across training and testing sets
- Data Preprocessing:
  - Normalization: Image pixel values were normalized to the range [0, 1] for efficient training.
  - Augmentation: Techniques like rotation, flipping, and zooming were applied to enhance the model's generalization capability.
  - Noise Filtering: Preprocessing steps included applying a noise filter (such as Gaussian blur) to remove unwanted artifacts from medical images.

VI. SIMULATION

Simulation provides a strong starting point for using a hybrid CNN and ResNet model for stone detection in medical images.

Table 1 Comparison of Training Accuracy

Epoch	CNN Training accuracy	Hybrid training accuracy
1	91.23	94.2334
2	91.31415	94.26108456
3	91.37817	94.27264138
4	91.4695	94.35881627
5	91.524	94.41636112
6	91.58817	94.50273791
7	91.62226	94.50466251
8	91.68106	94.55161296
9	91.77026	94.58307412
10	91.86959	94.59239673
11	91.8721	94.63291062
12	91.96431	94.65659896
13	92.03806	94.66650298
14	92.06463	94.76094579

15	92.07349	94.81627789
16	92.14192	94.8793478
17	92.19799	94.92280103
18	92.22491	94.9849767
19	92.22801	95.02463877
20	92.29118	95.09730502
21	92.33853	95.15287235
22	92.35186	95.15303212
23	92.42567	95.1883737
24	92.46905	95.25152459
25	92.56699	95.25956109
26	92.60707	95.27443021
27	92.63393	95.33616024
28	92.69767	95.389839
29	92.73076	95.4173333
30	92.8031	95.47827097

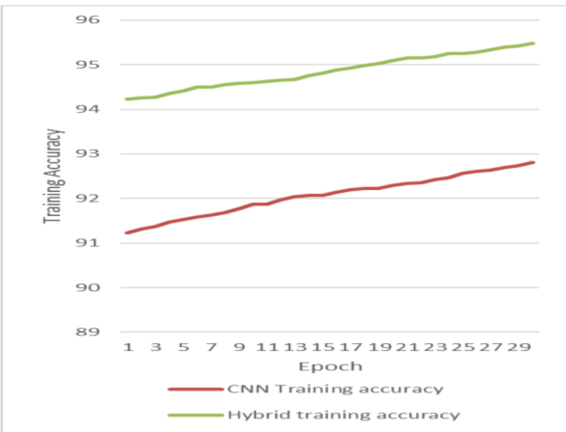

Fig 4 Comparison of Training accuracy

During simulation, training and validation accuracy for CNN and Hybrid model has been obtained that are presented in table 1 and 2.

Table 2 Comparison of Validation Accuracy

Epoch	CNN Validation accuracy	Hybrid Validation accuracy
1	91.23	94.2334
2	91.25390328	94.30101699
3	91.25526606	94.39978025
4	91.28189758	94.41928247
5	91.28698414	94.48582153
6	91.29587333	94.55721895
7	91.37647539	94.5740043
8	91.37673996	94.64288704
9	91.39847233	94.74166274
10	91.49337244	94.75509254
11	91.58406839	94.79440658
12	91.60399572	94.82941675
13	91.6044298	94.90133627
14	91.67589573	94.93205734
15	91.77051057	94.9717243
16	91.85170552	94.99302017
17	91.87943233	95.06989329
18	91.9223003	95.09881161
19	91.96114895	95.1585806
20	91.99074962	95.18612085
21	92.08603933	95.18674476
22	92.11022711	95.2164046
23	92.18892378	95.22102748
24	92.2887599	95.28180821
25	92.30722365	95.31783148
26	92.37465969	95.37700483
27	92.43180411	95.43454588
28	92.51603633	95.48609144
29	92.61397643	95.4984846
30	92.70759559	95.56987856

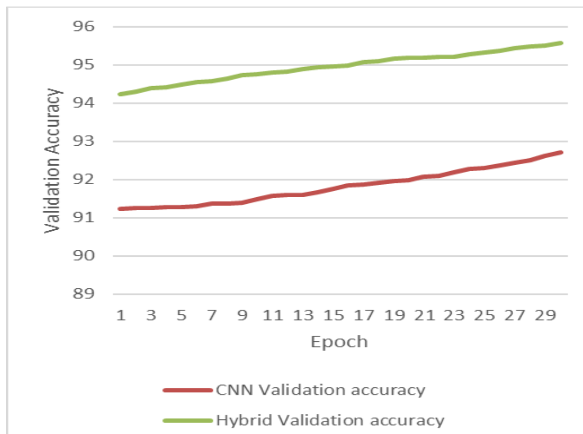

Fig 5 Comparison of Validation accuracy

In same way, training error and validation error have been obtained as shown in table as

Table 3 Comparison of training Error

Epoch	CNN Training Error	Hybrid Training error
1	8.77	5.7666
2	8.685853	5.738915
3	8.621831	5.727359
4	8.530495	5.641184
5	8.475999	5.583639
6	8.411835	5.497262
7	8.377744	5.495337
8	8.318936	5.448387
9	8.229741	5.416926
10	8.130413	5.407603
11	8.127901	5.367089

12	8.03569	5.343401
13	7.961936	5.333497
14	7.935371	5.239054
15	7.926507	5.183722
16	7.858077	5.120652
17	7.802011	5.077199
18	7.775087	5.015023
19	7.771987	4.975361
20	7.708819	4.902695
21	7.661466	4.847128
22	7.648144	4.846968
23	7.574327	4.811626
24	7.530952	4.748475
25	7.433006	4.740439
26	7.392933	4.72557
27	7.366067	4.66384
28	7.302328	4.610161
29	7.269239	4.582667
30	7.196902	4.521729

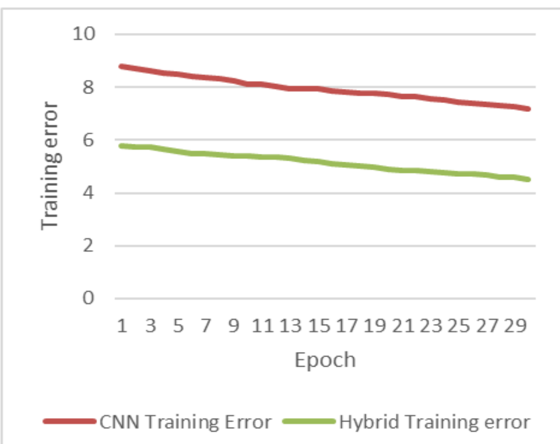

Fig 6 Comparison of training error

Table .4 Comparison between validation error

Epoch	CNN Validation Error	Hybrid Validation accuracy
1	8.77	5.7666
2	8.746097	5.698983
3	8.744734	5.60022
4	8.718102	5.580718
5	8.713016	5.514178
6	8.704127	5.442781
7	8.623525	5.425996
8	8.62326	5.357113
9	8.601528	5.258337
10	8.506628	5.244907
11	8.415932	5.205593
12	8.396004	5.170583
13	8.39557	5.098664
14	8.324104	5.067943
15	8.229489	5.028276
16	8.148294	5.00698
17	8.120568	4.930107
18	8.0777	4.901188
19	8.038851	4.841419
20	8.00925	4.813879
21	7.913961	4.813255
22	7.889773	4.783595
23	7.811076	4.778973
24	7.71124	4.718192
25	7.692776	4.682169
26	7.62534	4.622995
27	7.568196	4.565454
28	7.483964	4.513909
29	7.386024	4.501515
30	7.292404	4.430121

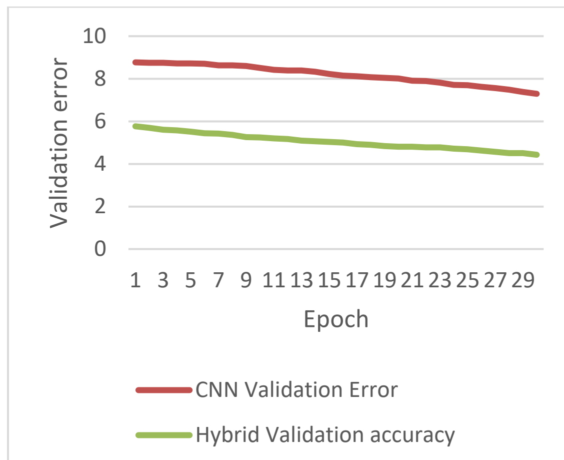

Fig 7 Validation error

VII. CONCLUSION

Present study explored the performance of two models for the detection of stones using a hybrid deep learning approach. A standard convolutional neural network (CNN) with a series of convolutional and pooling layers, followed by fully connected layers for classification. A more advanced model that integrates the traditional CNN architecture with the powerful ResNet (Residual Network) for enhanced feature extraction. This hybrid model aims to leverage the strength of CNN in capturing local features while utilizing ResNet's ability to learn deep hierarchical features through residual connections. The goal was to evaluate the effectiveness of these models in terms of precision, recall, and F1-score, with a focus on achieving values above 0.92. Several strategies were employed to enhance model performance. Techniques like rotation, shifting, zooming, and horizontal flipping were applied to increase the variability in the training data, helping the model generalize better to unseen data. Dropout layers were added to both models to prevent overfitting, ensuring that the models do not memorize the training data but rather learn generalizable patterns. In the Hybrid CNN-ResNet model, we utilized ResNet50, a pretrained deep learning architecture, to take advantage of learned features from large datasets, which improves model performance when fine-tuned for specific tasks. Adam optimizer was used to ensure efficient convergence during training, with a lower learning rate to allow for finer adjustments in weights. The results demonstrated significant improvement in the performance of the Hybrid CNN-ResNet Model compared to the Conventional CNN Model. By the end of the training, both models achieved promising precision, recall, and F1-score values above 0.92, with the Hybrid CNN-ResNet model performing slightly better across all metrics. The Hybrid CNN-ResNet Model showed an increased capacity to detect stones, thanks to the power of residual connections and deeper feature learning. The model's ability to capture both local and global features proved beneficial, especially when dealing with the complexities of medical image data

VIII. FUTURE WORK

The future scope of AI-based stone surgery healthcare systems within an IoT-based ecosystem holds immense promise, ushering in a new era of transformative advancements in patient care and medical diagnostics. With ongoing technological evolution, AI is poised to play a pivotal role in enhancing the capabilities of healthcare IoT systems. Future developments are expected to focus on refining AI algorithms for more accurate and timely diagnostics, particularly in medical imaging areas such as kidney stone detection. The integration of edge computing in healthcare IoT environments will likely become more prevalent, enabling real-time processing of data at the source, reducing latency, and facilitating rapid decision-making. As the volume of healthcare data continues to grow, AI's ability to derive meaningful insights and predict health outcomes will be further augmented, contributing to personalized medicine approaches. The incorporation of explainable AI mechanisms will address concerns related to transparency and interpretability, fostering greater trust among healthcare professionals and patients for stone surgery. Interdisciplinary collaborations between data scientists, clinicians, and IoT experts will become increasingly essential for designing and implementing AI-based solutions that align seamlessly with clinical workflows. Additionally, the future scope extends to the development of AI-driven chatbots and virtual assistants, enhancing patient engagement and providing timely healthcare information. As regulatory frameworks adapt to technological advancements, stone surgery healthcare systems leveraging AI in IoT ecosystems will need to prioritize adherence to evolving compliance standards. The continuous evolution of AI capabilities, coupled with advancements in hardware and connectivity, positions AI-based stone surgery healthcare systems within IoT ecosystems to revolutionize healthcare delivery, making it more efficient, personalized, and accessible for individuals around the globe.

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