

Using Block chain Systems for Encrypting Individual Medical Records

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ABSTRACT: Artificial intelligence (AI) has been utilized in the healthcare sector for decades, supporting a extensive collection of proposals. Through machine learning and AI algorithms, it has become possible to improve diagnostics, initial conduct tactics, and improve enduring results. During the COVID-19 pandemic, AI models were notably employed to predict symptoms, track the virus's spread, and accelerate research and treatment using medical data. Despite these advancements, deploying AI in real-time, real-world healthcare settings presents significant challenges. One major issue is the reluctance of organizations to share sensitive patient data with third parties due to privacy concerns. Additionally, the fragmented nature of enduring information transversely unlike healthcare schemes makes it difficult to develop a generalized predictive model.

To talk these subjects, this paper proposes a solution that integrates block chain and AI technologies. Block chain can ensure secure and controlled access to medical data, while federated learning—a decentralized AI approach—can enable the development of robust, real-time models without compromising data privacy.

Keywords: AI, MEDICAL, real time, Covid

1. INTRODUCTION

Recent advancements in artificial intelligence (AI), particularly in machine learning and deep learning, have led to remarkable innovations in the healthcare sector—especially within radiology. The COVID-19 pandemic further accelerated the development of

AI-based solutions, many of which produced promising outcomes. Radiological imaging, such as X-rays and Computed Tomography (CT) scans, has remained extensively rummage-sale in detecting various inflammatory lung diseases ([1],[2],[3],[4]). Blockchain technology has added a new dimension to the healthcare landscape by enhancing data security and ensuring data integrity. It supports the creation of standardized and formalized smart contracts for secure access to medical data. This is chiefly pertinent once allocating by electronic health records (EHR), which involve complex workflows and make it difficult to trace who performed which task and when. Blockchain addresses this issue by timestamping every action and associating it with a specific identity. These annals remain dispersed athwart all participating nodes in the network, safeguarding that a little ups and downs made are synchronized and visible across all locations globally. This appliance assurances information honesty and clearness without requiring manual oversight [5]. Federated Learning (FL) is a contraption knowledge method that allows decentralized training crossways manifold advantage plans however preservative user privacy. Instead of transferring raw data, the model is trained locally on each device using user-specific data. The nearby skilled replicas are formerly directed to a dominant attendant wherever they are combined to update the global model. The updated model is subsequently redistributed to all devices [6]. This collaborative method allows for effective AI prototypical exercise deprived of revealing secluded statistics. Initially used in applications involving mobile and edge devices [7],

FL abstains lately increased important impetus in healthcare. Educations devise exposed that replicas trained using federated learning often achieve higher accuracy compared to persons skilled in isolated settings ([8], [9]).

II. LITERATURE REVIEW

Developing clinical-decision support systems for medical imaging poses reliability and interpretability challenges. Here, we develop an intricate learning-based diagnostic tool for identifying individuals with common, curable retinal disorders that cause blindness. Our methodology makes use of transfer learning, a technique which uses a less amount of information than traditional methods to train a network of neural cells. By using our method on a dataset of optical coherence tomography pictures, we show that it can classify diabetic macular edema and age-related macular degeneration with performance on par with human experts. By emphasizing the areas that the neural network has identified, we also offer a diagnostic that is clearer and easier to understand. Developing clinical-decision support systems for medical imaging poses reliability and interpretability challenges. Here, we develop an intricate learning-based diagnostic tool for identifying individuals with common, curable retinal disorders that cause blindness. Our methodology makes use of transfer learning, a technique which uses a less amount of information than traditional methods to train a network of neural cells. By using our method on a dataset of optical coherence tomography pictures, we show that it can classify diabetic macular edema and age-related macular degeneration with performance on par with human experts. We also provide a more convenient and comprehensible diagnosis by highlighting the regions that the neural network has detected. Using chest X-ray pictures, we further illustrate our AI system's generalizability for diagnosing juvenile pneumonia. In the end, this tool could help speed up the diagnosis and referral of these curable illnesses, enabling earlier treatment and better clinical results.

III. EXISTING SYSTEM

Non-natural astuteness techniques are already delivering promising results in diagnosing various critical diseases through the analysis of medical images. Unique of the key roles of AI in healing imaging is to serve as a choice provision instrument for clinicians, enabling faster, more accurate, and more precise diagnoses. Among AI approaches, deep learning has emerged as particularly effective in disease detection from medical images.

Sekeroglu and Ozsahin developed a technique by means of Convolutional Neural Networks (CNNs) to become aware of COVID-19 from chest X-rays. Their prototypical categorized imageries into three categories—healthy, pneumonia, and COVID-19—achieving an impressive accuracy of 98.50% even with a small, imbalanced dataset [10]. Similarly, Jain et al. planned a deep learning-based technique to differentiate amid healthy individuals and COVID-19 patients using 6,432 chest X-ray samples. After testing numerous deep learning replicas, they found that the Xception architecture delivered the highest accuracy at 97.97%, proving effective in COVID-19 diagnosis [11].

Ozturk et al. introduced a model employing both binary and multiclass classification. In the binary classification task (COVID-19 vs. No-Findings), their model achieved 98.08% accuracy, while in the multiclass task (COVID-19 vs. No-Findings vs. Pneumonia), it achieved 87.02%. They utilized the YOLO object detection system with the DarkNet model, which proved helpful for initial screening by radiologists [12].

On the data management side, Linn and Koo presented a simple yet powerful application of blockchain technology for storing healthcare data. Their system proposes recording a patient's complete medical history—from birth records to wearable device data, lipid profiles, and MRI scans—on a secure blockchain platform [14]. Liang et al. added that such systems can permit consumers to selectively segment statistics by healthcare breadwinners and assurance corporations for

remedial facilities or insurance quotes. This user-centric model ensures that persons uphold filled mechanism above their statistics, supporting both privacy and potential contributions to medical research [15].

Federated Learning (FL) offers significant advantages for healthcare providers by enhancing the accuracy and robustness of AI representations, building them additionally fit for real-time, practical deployment. Importantly, FL allows training to be done collaboratively across institutions without sharing sensitive data, thus maintaining privacy while saving time and cost. This approach ensures all the benefits of advanced AI without compromising data security.

DISADVANTAGES OF EXISTING SYSTEM:

Our solution is not a differential privacy mechanism that modifies patient data to confuse the hospital records.

An existing system is not implements block chain-Federated Learning Architecture.

IV. PROPOSED SYSTEM

Initially, hospitals, universities, and pharmaceutical companies operated independently, training AI models in isolation. However, with the adoption of federated learning, these individually trained models are now shared with a central federated server, where they learn collaboratively without compromising data privacy. In this setup, devices connected to the federated server send only their locally trained models—not raw data—to the server. The server aggregates these models, typically through averaging, to form a single, more robust model. This process is repeated iteratively until a high-quality model is achieved. This planning deals with numerous important benefits:

Collaborative Learning: As models are trained collectively, they improve over time, yielding additional precise consequences smooth with previously unseen data.

Reduced Latency: Predictions are made locally on devices using the updated model, minimizing response time.

Remote Insights: Data insights can be obtained without needing physical access to the data location, making the process more flexible.

Data Privacy: Privacy is preserved throughout the process since raw data never leaves the local device—only the trained models are shared.

Off the additional influence, block chain technology facilitates secure and transparent data access for researchers, clinicians, and institutions through a decentralized network. It ensures data integrity, non-repudiation, and the protection of patients' private information. The blockchain-based data access process works as follows:

The user registers and creates account on the platform. The user requests access to a specific dataset or digital asset. A smart contract verifies whether the requested data is available in the blockchain ledger. If available, it reserves the resource and notifies the user.

The user reviews the access conditions and signs the contract. Upon validation, the user is charged a transaction fee based on the smart contract terms, and a usage token is issued.

This method lets see-through tracking of who accessed the data, when it was accessed, and for what purpose—enhancing both security and accountability.

ADVANTAGES OF PROPOSED SYSTEM:

Privacy is most important, particularly in the circumstance of medical imaging data. As the AI based model is getting traction these days especially in the meadow of medical imaging, protecting the private information is necessary before rummage-sale in the real time environment.

The healthcare records are maintaining using blockchain which are very safe and secure.

V. MODULE DESCRIPTION

Hospital Module

Infirmaries are accountable for gathering patient statistics, including: Patient ID (pid), name (pname), address (paddress), contact number (pcno), email (pemail), pulse rate (ppulse), ECG (pecg), and symptoms (pSymptoms). Hospitals can upload symptom-related documents (with digital signatures) and patient images to the cloudlet.

All patient data—except for the patient name—is encrypted before being uploaded.

Hospitals can view all collected patient data in encrypted format, along with associated digital signatures.

Healthcare Cloud Module

The cloud server acts as the central platform for data management and provides the following functionalities: Stores data from wearable devices. Displays and authorizes both patient and doctor profiles. Allows viewing of all encrypted patient data uploaded from the cloudlet. Handles and authorizes patient data access requests. Monitors intruder activities and logs intrusion attempts. Displays recovered patient data. Visualizes analytical charts: Number of patients with the same symptoms (Symptom Name vs. Number of Patients). Amount of patients referred concerning the same doctor (Doctor Name vs. Number of Patients).

3. Patient Module

Patients have access to the following features: Registration and login. View personal profile. Request permission from the cloudlet to access their encrypted data. View access permission responses. Access and review their medical data. Choose a doctor from a dropdown menu and send medical data for consultation. View doctor responses and prescriptions.

Verify, recover, or erase their individual information from the system.

Doctor Module

Doctors are responsible for the following operations: Register and login to the system. View and update personal profiles. Access patient details and provide medical solutions including: Medicine recommendations. Medical prescription details. View all medical prescriptions provided to patients.

System Architecture

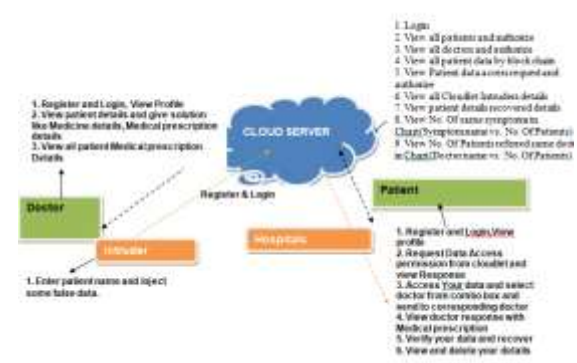
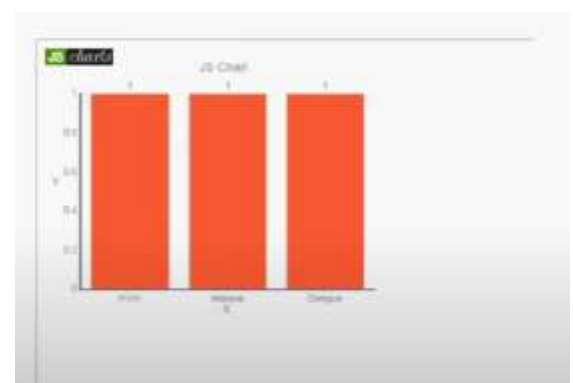


Fig 1. System Architecture

VI.RESULT



The incorporation of block chain and AI, particularly federated learning, has shown promising outcomes in addressing the key tests related through discretion, data sharing, and model generalization in the healthcare subdivision. The anticipated method safeguards that subtle patient statistics rests secure and localized while still contributing to the training of an accurate and

globally applicable AI model. Through decentralized learning, the system successfully aggregates knowledge from multiple healthcare institutions without exposing raw data. This methodology leads to improved prediction accuracy, faster response times, and enhanced trust among stakeholders. Preliminary evaluations indicate that federated AI prototypes can attain presentation heights similar to or better than traditional centralized models, even when trained on fragmented and distributed datasets.

VII.CONCLUSION

In conclusion, the mixture of chunk chain and joined knowledge offers a viable and secure solution for the deployment of AI in real-world healthcare environments. By preservative information confidentiality and allowing co-operative knowledge, this method overcomes the limitations posed by data silos and security concerns. It empowers healthcare organizations to participate in the development of advanced AI models without compromising patient confidentiality. This outline not merely improves the scalability and reliability of AI applications in healthcare but also sets a foundation for ethical and transparent data handling practices in future medical research and diagnostics.

REFERENCES

1. Choe, J., Lee, S.M., Do, K.H., Lee, G., Lee, J.G., Lee, S.M. and Seo, J.B., 2019. Deep learning-based image conversion of CT reconstruction kernels improves radiomics reproducibility for pulmonary nodules or masses. *Radiology*, 292 (2), pp. 365–373.
2. Kermany, D.S., Goldbaum, M., Cai, W., Valentim, C.C., Liang, H., Baxter, S.L., McKeown, A., Yang, G., Wu, X., Yan, F. and Dong, J., 2018. Identifying medical diagnoses and treatable diseases by image-based deep learning. *Cell*, 172 (5), pp. 1122–1131.
3. Negassi, M., Suarez-Ibarrola, R., Hein, S., Miernik, A. and Reiterer, A., 2020. Application of artificial neural networks for automated analysis of

cystoscopic images: a review of the current status and future prospects. *World Journal of Urology*, pp. 1–10.

4. Gulshan, V., Peng, L., Coram, M., Stumpe, M.C., Wu, D., Narayanaswamy, A., Venugopalan, S., Widner, K., Madams, T., Cuadros, J. and Kim, R., 2016. Growth and authentication of a profound education procedure for discovery of diabetic retinopathy in retinal fundus snapshots. *Jama*, 316 (22), pp. 2402–2410.