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Bridging Diagnostic Gaps in Stroke Care: Implementing AI Medical Imaging Solutions in Resource-Limited Indian Settings

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Abstract: Delays in diagnosis, restricted access to neuroimaging equipment, and a lack of qualified radiologists—particularly in rural and semi-urban areas—present serious obstacles to stroke care in India. To close these diagnostic gaps, this study investigates the use of medical imaging technologies based on artificial intelligence (AI). With an emphasis on their adaptation to low-resource healthcare situations, we investigate the implementation of deep learning models for automated stroke diagnosis and classification utilizing CT and MRI data.

This work uses anonymized imaging data from Indian hospitals to train convolutional neural networks (CNNs) and U-Net architectures to locate ischemic and haemorrhagic strokes. Sensitivity, specificity, and processing time are the performance measures. Beyond building the model, the paper takes a look at practical considerations for real-world implementation: infrastructure limitations, regulatory challenges, and clinician-AI integration.

The findings drive that an AI model can attain high diagnostic accuracy and offer real-time support in a nonexpert setting. This paper argues that with localized datasets, policy support, and appropriate training, AI-powered imaging can revolutionize stroke diagnosis to drastically better clinical outcomes in underprivileged Indian communities.

Key: CNN, Stroke Care, Medical Imaging, CT, MRI and AI

1. Introduction

Stroke is a major global cause of death and permanent disability, and it disproportionately affects low- and middle-income (LMIC) nations like India. Over 1.8 million stroke cases are reported in India alone each year; a significant percentage of fatalities and long-term impairment are linked to insufficient acute care and delayed diagnosis (Pandian & Sudhan, 2013) [1]. Effective stroke care depends on timely neuroimaging, but there are significant differences in the availability of imaging technology and specialized radiologists in the nation's urban and rural areas (Kaur et al., 2022) [2].

Automating stroke diagnosis and medical image interpretation has become possible because to recent developments in deep learning and artificial intelligence (AI). Real-time analysis of computed tomography (CT) and magnetic resonance imaging (MRI) data by AI-enabled devices helps physicians make quick and precise decisions. These methods hold particular promise in settings with low resources, where specialized knowledge is hard to come by and delayed diagnosis frequently leads to worse results (Chilamkurthy et al., 2018) [3].

Deep learning models including convolutional neural networks (CNNs) and U-Net architectures have been shown in several studies to perform at par with trained radiologists in the detection of Ischemic and hemorrhagic strokes (Litjens et al., 2017; Monteiro et al., 2020)[4,5]. The problem is that most of these solutions have been developed using datasets from high-income settings and may not generalize well for the Indian healthcare system due to differences in imaging protocols and infrastructure limitations apart from patient demographics.

It implements AI-powered tools for stroke diagnosis and does the tailoring for the resource-constrained Indian settings. Key challenges: model adaptation, infrastructural compatibility, and clinician adoption are also addressed in this paper. A framework is proposed here for the deployment of AI-driven imaging solutions to bridge the diagnostic gap in rural and underserved areas.. The objective is to enhance outcomes throughout India's heterogeneous healthcare system and enable fair access to high-quality stroke diagnostics.

2. Literature Survey

Over the past ten years, there has been a notable increase in the application of artificial intelligence (AI) in medical imaging since multiple studies have shown that AI may enhance clinical judgment and increase diagnostic precision. Deep learning models like convolutional neural networks (CNNs) have demonstrated exceptional performance in identifying and classifying stroke lesions from CT and MRI scans, especially in neuroimaging..

A major study by Litjens et al. (2017) [6] covered deep learning techniques in several medical imaging applications and highlighted the use of CNNs for such tasks as tumor detection, organ segmentation, and identifying vascular abnormalities. From that base, a number of stroke-specific models have come. For example, Monteiro et al. (2020) [5] applied U-Net architectures to segment traumatic brain injury lesions, bringing out the model's appropriateness for complex neuroimaging data. These segmentation frameworks have since been converted to detect ischemic and hemorrhagic strokes with high sensitivity.
Chilamkurthy et al., 2018 [7] used Indian hospital data to develop and validate a deep learning algorithm to detect critical findings on head CT—intracranial hemorrhage included. Their work demonstrates the viability of large-scale deployment and is notable as one of the first validations of AI for radiological diagnosis in an Indian healthcare system.
AI provides a scalable solution to alleviate the radiology deficit in settings with limited resources. The systemic obstacles and digital preparedness needed to integrate AI in Indian clinical practice were covered by Jha and Topol (2020) [8]. Similar to this, Kaur et al. (2022) [9] described the particular difficulties in providing stroke care in India, pointing out that rural hospitals frequently do not have prompt access to neuroimaging and stroke specialists, which could lead to a diagnosis gap that AI could fill.
Notwithstanding these developments, the majority of AI models are trained on high-income country datasets, and they could not function as well on data from LMICs like India. Model accuracy can be greatly impacted by domain shift brought on by variations in scanner types, imaging techniques, and patient demographics (Gichoya et al., 2022) [10]. This emphasizes the necessity of context-aware AI systems that are built for deployment in low-resource environments and trained on local datasets.
According to recent research, there is increasing agreement that AI has the ability to make stroke diagnosis more accessible to all. Nevertheless, there are still few studies

that concentrate on clinical integration, model adaption, and infrastructure compatibility in Indian contexts. By assessing AI-based imaging solutions designed especially for the opportunities and limitations of India's healthcare system, this article seeks to close this gap.

3. Materials and Methods

3.1 Data Collection and Preprocessing

Three tertiary care hospitals in India—one in Delhi, one in Lucknow, and one in Jharkhand—provided anonymized, retrospective CT and MRI brain imaging datasets for this investigation. 700 MRI and 1,500 CT scans of verified stroke patients—both ischemic and hemorrhagic—were included in the collection. In compliance with national biomedical research guidelines (ICMR, 2017), institutional data-sharing agreements and ethical approval were obtained [11]. To guarantee uniformity, every image was preprocessed and translated to the standard DICOM format. Skull stripping, bias field correction, voxel intensity normalization, and scaling to a consistent 256x256 resolution were all preprocessing procedures. Two skilled radiologists' manual annotations served as the ground truth for both model validation and training.

3.2 AI Model Architecture

There were two varieties of deep learning architectures used:

- A 2D Convolutional Neural Network (CNN) that uses CT slices to classify stroke types (ischemic versus hemorrhagic).
- A semantic segmentation model based on U-Net for identifying stroke lesions on MRI scans, specifically the ischemic core and bleeding regions.

TensorFlow and Python were used to create the model. The data was divided into subgroups for testing (15%), validation (15%), and training (70%). To increase model generalizability—which is crucial for low-volume rural datasets—data augmentation techniques like rotation, flipping, and Gaussian noise were used [12].

3.3 Evaluation Metrics

Standard performance criteria were used to assess the models, including accuracy, sensitivity, specificity, Dice similarity coefficient (DSC), and area under the ROC curve (AUC). Robustness was evaluated in various healthcare scenarios worldwide and by site (rural, semi-urban, and urban).

3.4 Deployment Framework

TensorFlow Lite and NVIDIA Jetson Nano modules were used to deploy models on edge devices in order to verify their viability in low-resource scenarios. These setups mimicked real-world scenarios without dependable internet access or powerful GPUs. Recorded were inference times, resource usage, and clinician usability comments.

3.5 Validation and Human-AI Collaboration

A reader research with ten general practitioners and three radiologists was carried out to evaluate the practical clinical impact. Participants examined 100 examples that were chosen at random, both with and without AI support. Consistent with the findings of Esteva et al. (2019), the results demonstrated notable enhancements in diagnostic confidence and decreased time-to-decision with AI help, especially in non-specialist settings [13].

4. India’s and Digital Health

With major policy and technology developments that enhance access, affordability, and quality of care, India is embarking on a revolutionary journey to digitize its healthcare system. As part of the larger Ayushman Bharat Digital Mission (ABDM) and Digital India programs, integrating digital technology and artificial intelligence (AI) into the healthcare ecosystem has been given top priority.

4.1 Policy Framework and Infrastructure

Launched in 2021, the Ayushman Bharat Digital Mission (ABDM) offers a fundamental digital health architecture that consists of elements including a national health registry, electronic health records (EHRs), and the Ayushman Bharat Health Account (ABHA) (MoHFW, 2021). AI-based clinical decision support systems may be seamlessly integrated, and data exchanged thanks to this interoperable architecture, which is especially helpful in under-resourced and rural locations.

The adoption of AI-powered medical imaging across various healthcare setups is facilitated by the National Health Stack and National Digital Health Blueprint (NDHB), which suggest critical enablers like telemedicine, cloud-based imaging repositories, and standardized health data formats (NITI Aayog, 2019) [15].

4.2 AI Integration and Government Initiatives

AI has been acknowledged by NITI Aayog and the Ministry of Electronics and Information Technology (MeitY) as a strategic instrument to enhance healthcare delivery. The "National Strategy for Artificial Intelligence" study, published by NITI Aayog in 2018, identified healthcare, especially diagnostics, as the central area of concentration for AI adoption in India. To overcome the lack of qualified specialists in rural areas, it strongly emphasizes using AI for imaging data screening, triage, and interpretation [16].

In partnership with private and academic institutions, pilot projects like AI-based screening for diabetic retinopathy and tuberculosis have already been successfully implemented, setting the stage for the expansion of AI-enabled stroke detection (Reddy et al., 2021). [17]

4.3 Digital Health Challenges and Opportunities[18]

Regardless of the efforts put forth towards digital health law policy, there remains a gap in the full realization potential capabilities of digital health. These gaps include uneven digital skills among a range of healthcare workers, issues regarding internet availability, apprehensions about data security, and absence of legislation dealing with artificial intelligence or AI policies.However, in addition to the growing availability of reasonably priced edge computing solutions, the Bharat Net initiatives still have the potential to enhance internet infrastructure. These elements may result in more extensive AI uses in stroke treatment.

The application of AI in medical imaging systems can ensure efficient stroke identification and management in low resource areas by integrating mobile based diagnostic tools within India's cloud based healthcare infrastructure.

5. Results

5.1 Classification Accuracy

With a sensitivity of 92.8% for ischemic strokes and 95.6% for hemorrhagic strokes, the 2D CNN model created for the purpose of classifying stroke types (ischemic vs. hemorrhagic) using CT scans had an overall accuracy of 94.2%. Excellent model discrimination was indicated by the area under the ROC curve (AUC), which was

0.96. Despite slightly decreased sensitivity in rural datasets due to changes in imaging techniques and worse picture quality, model performance was consistently strong throughout the three testing sites. These findings support the viability of implementing such models in the Indian healthcare system and are consistent with those found in related AI-based stroke research (Chilamkurthy et al., 2018; Monteiro et al., 2020) [3, 5].

5.2 Lesion Segmentation Performance

For ischemic lesions and hemorrhagic regions on MRI, the U-Net segmentation model obtained a Dice Similarity Coefficient (DSC) of 0.87 and 0.91, respectively. Even in situations with motion disturbances or low contrast images, which are frequent in low-resource environments, the model showed resilience in detecting lesion boundaries.

The AI segmentation model helped radiologists reduce their average interpretation time by 23% without sacrificing diagnostic quality, according to a comparative analysis. [6,13] This is consistent with earlier research showing that AI assistance can greatly improve radiological efficiency (Litjens et al., 2017; Esteva et al., 2019).

5.3 Deployment Performance

With average inference times of 2.4 seconds per CT scan and 3.8 seconds per MRI volume, the models were effectively implemented on edge devices and fell well within reasonable clinical timelines. Metrics of power and memory usage showed that the system worked with common hardware found in district hospitals in India.

During field trials, clinician feedback revealed that the interface was user-friendly and increased diagnostic confidence, particularly for non-specialist medical officers. For neurological disorders, more than 80% of rural doctors said they were more open to using AI techniques.

5.4 Human-AI Collaboration Study

When compared to unaided review, general practitioners using the AI technology improved diagnostic accuracy by 17% in the clinical reader research. Although to a lesser degree, radiologists also profited, demonstrating the tool's value as a decision support system rather than a substitute for clinical knowledge.

6. Conclusion

This study emphasizes how artificial intelligence (AI)-enabled medical imaging can improve stroke detection, especially in Indian healthcare settings with minimal resources. The suggested models showed excellent diagnostic accuracy and segmentation performance by utilizing deep learning techniques applied to CT and MRI scans, while still being computationally economical for deployment on inexpensive edge devices. Even in remote locations with little radiological experience, the results confirm that AI can be a potent auxiliary tool for frontline healthcare providers, allowing for early stroke case diagnosis and triage. Bridging diagnostic inequalities can be accomplished in a scalable and sustainable way by integrating such systems into India's developing digital health framework, which is centered by the Ayushman Bharat Digital Mission.

However, to ensure ethical and fair use, successful adoption will necessitate ongoing investments in infrastructure, local data curation, physician training, and regulatory supervision. Future research should concentrate on developing context-specific user interfaces for rural and semi-urban healthcare settings, integrating

multimodal data (such as clinical history and ECG), and conducting real-world clinical trials in order to increase the model's capabilities.
AI-driven solutions provide a way to democratize high-quality stroke care and lessen the substantial morbidity and mortality burden linked to delayed detection by coordinating technical innovation with India's public health priorities.

References

1. Pandian, J. D., & Sudhan, P. (2013). Stroke epidemiology and stroke care services in India. Journal of Stroke, 15(3), 128–134.
2. Kaur, P., Rana, T., Singh, M., & Kalra, S. (2022). Stroke care in India: Challenges and opportunities for AI-based interventions. *Journal of Clinical Neuroscience*, *97*, 34–39.
3. Chilamkurthy, S., Ghosh, R., Tanamala, S., Biviji, M., Campeau, N. G., Venugopal, V. K., & Warier, P. (2018). Development and validation of deep learning algorithms for detection of critical findings in head CT scans. *The Lancet*, *392*(10162), 2388–2396. https://doi.org/10.1016/S0140-6736(18)31645-3
4. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & van der Laak, J. A. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, *42*, 60–88.
5. Monteiro, M., Newcombe, V. F. J., Mathieu, F., Adatia, K., Kamnitsas, K., Ferrante, E.& Glocker, B. (2020). Multiclass semantic segmentation and quantification of traumatic brain injury lesions on head CT using deep learning. *Radiology: Artificial Intelligence*, *2*(3), e190109. https://doi.org/10.1148/ryai.2020190109
6. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & van der Laak, J. A. (2017). A survey on deep learning in medical image analysis. *Medical Image Analysis*, *42*, 60–88.
7. Chilamkurthy, S., Ghosh, R., Tanamala, S., Biviji, M., Campeau, N. G., Venugopal, V. K., ... & Warier, P. (2018). Development and validation of deep learning algorithms for detection of critical findings in head CT scans. *The Lancet*, *392*(10162), 2388–2396. https://doi.org/10.1016/S0140-6736(18)31645-3
8. Jha, S., & Topol, E. J. (2020). Adapting artificial intelligence in India: From algorithm to implementation. The Lancet Regional Health – Southeast Asia, 1, 100001.
9. Kaur, P., Rana, T., Singh, M., & Kalra, S. (2022). Stroke care in India: Challenges and opportunities for AI-based interventions. Journal of Clinical Neuroscience, 97, 34–39.
10. Gichoya, J. W., Banerjee, I., Bhimireddy, A. R., Burns, J. L., Celi, L. A., Chen, L& Lungren, M. P. (2022). AI recognition of patient race in medical imaging: a modeling study. The Lancet Digital Health, 4(6), e406–e414. https://doi.org/10.1016/S2589-7500(22)00063-2
11. ICMR. (2017). National Ethical Guidelines for Biomedical and Health Research Involving Human Participants. *Indian Council of*

Medical Research, Government of India.

12. Perez, L., & Wang, J. (2017). The Effectiveness of Data Augmentation in Image Classification using Deep Learning. *arXiv preprint*, arXiv:1712.04621. https://arxiv.org/abs/1712.04621
13. Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K.,& Dean, J. (2019). A guide to deep learning in healthcare. *Nature Medicine*, *25*(1), 24–29. https://doi.org/10.1038/s41591-018-0316-z
14. Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, *25*, 44–56.
15. NITI Aayog. (2019). National Digital Health Blueprint. Government of India.
16. NITI Aayog. (2018). National Strategy for Artificial Intelligence – #AIforAll. https://www.niti.gov.in/strategy-ai
17. Reddy, S., Fox, J., & Purohit, M. P. (2021). Artificial intelligence-enabled healthcare delivery: opportunities, challenges, and the Indian roadmap. BMJ Innovations, 7(3), 540–546. https://doi.org/10.1136/bmjinnov-2020-000598
18. Ministry of Health and Family Welfare (MoHFW). (2021). Ayushman Bharat Digital Mission Blueprint. Government of India. https://abdm.gov.in