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MINISTRY OF ELECTRONICS AND INFORMATION TECHNOLOGY

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COMPENDIUM

Real-World Impact of AI in Health

World Health Organization

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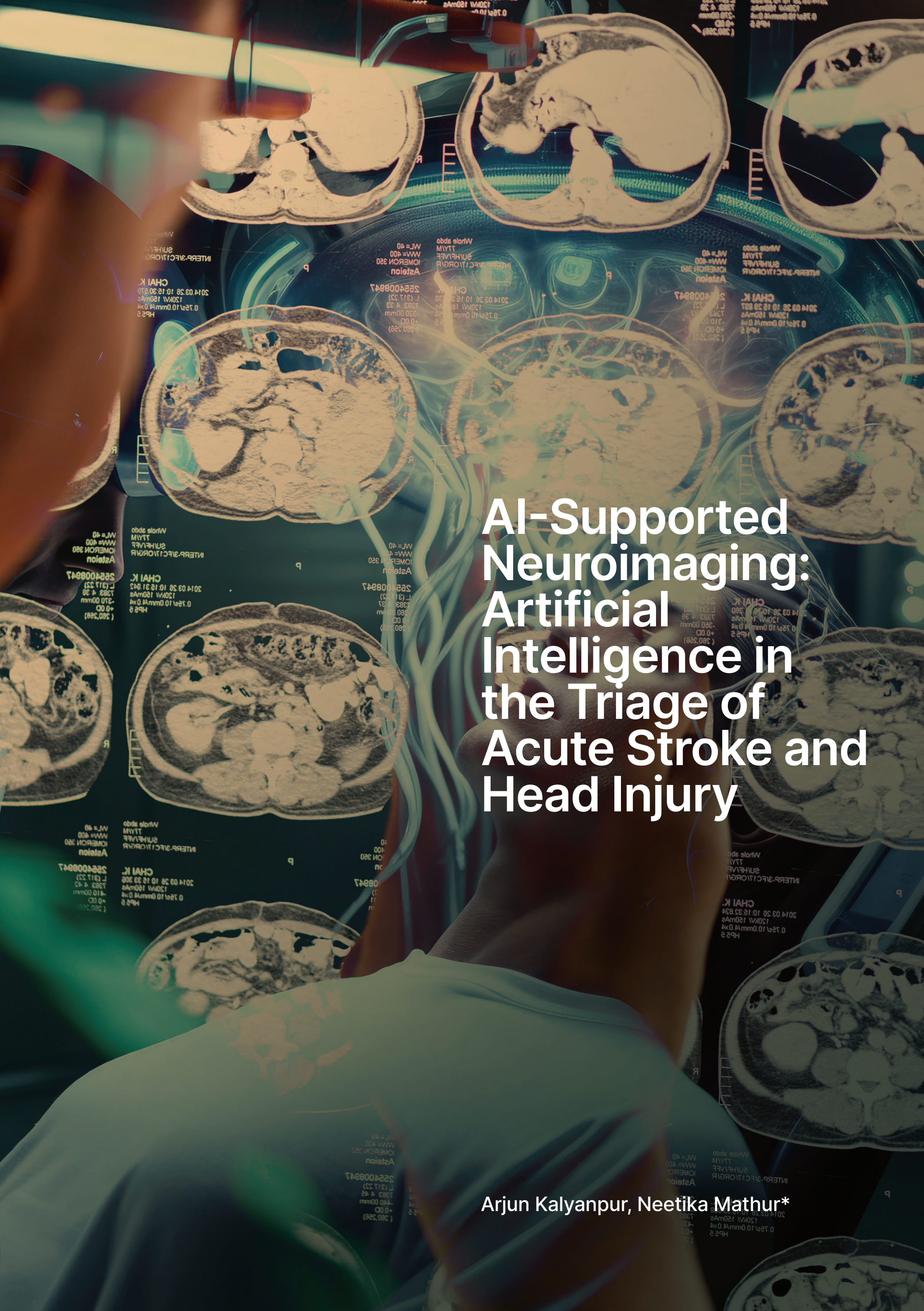
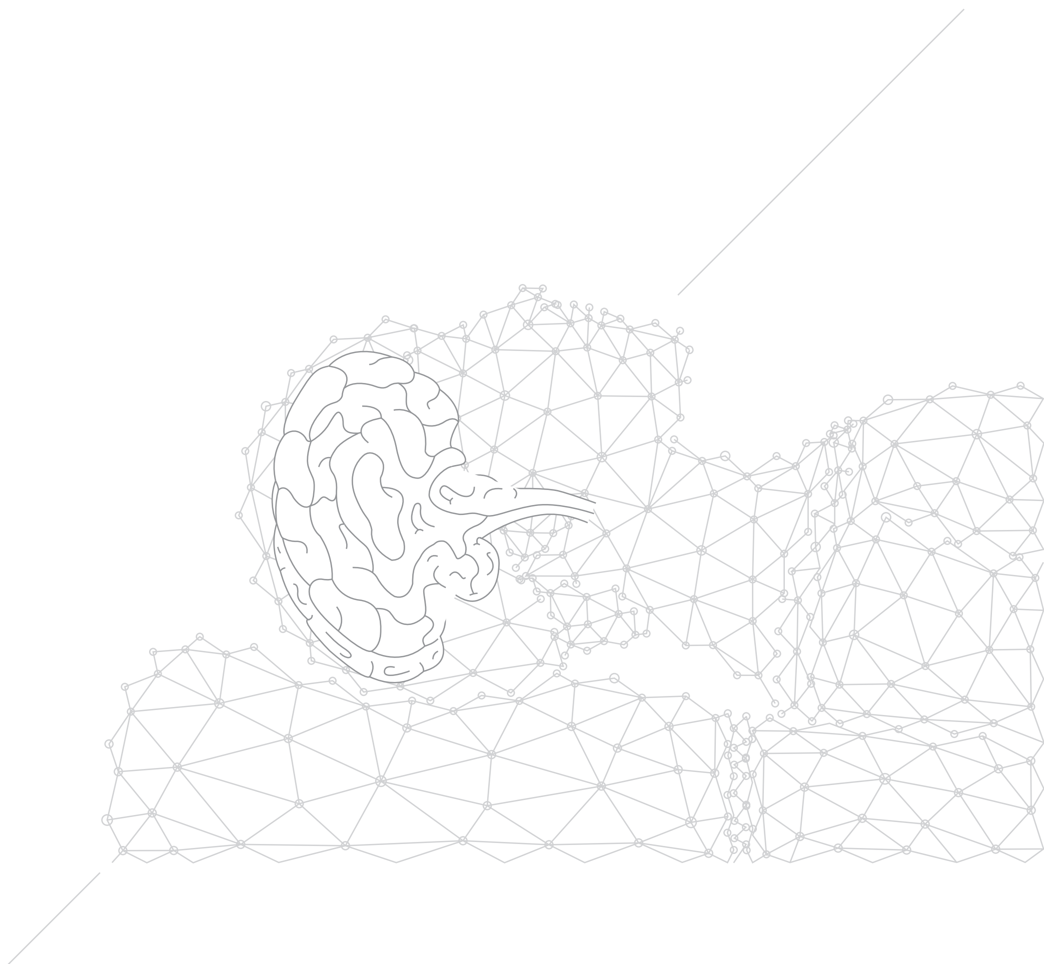


AI-Supported Neuroimaging: Artificial Intelligence in the Triage of Acute Stroke and Head Injury

Arjun Kalyanpur, Neetika Mathur*



Use Case 10

AI FOR COMPUTER VISION IN HEALTH

AI-Supported Neuroimaging: Artificial Intelligence in the Triage of Acute Stroke and Head Injury

Arjun Kalyanpur, Neetika Mathur*

Abstract

Stroke and head injury remain major causes of mortality and disability in India and globally. In acute stroke care, timely diagnosis is closely linked to clinical decision pathways, while early identification of intracranial bleeding in head injury informs urgent management decisions. This use case describes the operational use of an artificial intelligence (AI) enabled tool, Neural Assist, integrated within a teleradiology workflow to support radiologists in the triage and interpretation of non-contrast head CT scans for suspected stroke and head injury.

Non-contrast digital head CT scans from hospitals across the country are uploaded to an AI-enabled, cloud-based telereporting workflow platform, RADspa, which integrates the radiology information system (RIS) and picture archiving and communication system (PACS). The embedded AI algorithm automatically analyses images to identify features requiring urgent attention, including intracranial hemorrhage, hemorrhage type, midline shift (brain swelling), skull fracture, and vessel-density patterns associated with ischaemia. Suspected positive cases are flagged within the radiologist's worklist to support prioritisation and faster triage. In internal validation, NeuralAssist was reported to detect haemorrhage with approximately 89% sensitivity and 91% specificity, classify haemorrhage type with approximately 90% accuracy, identify midline shift with approximately 87% sensitivity and 88% specificity, dense MCA with approximately 87% sensitivity and 92% specificity. and detect skull fractures with approximately 90% sensitivity and 93% specificity. AI outputs are provided as decision support, while final interpretation and reporting remain the responsibility of qualified radiologists, and validated reports are distributed to hospitals through the same platform.

Reported performance metrics from internal validation datasets indicate sensitivity and specificity ranges across multiple detection tasks. These figures should be interpreted as technical performance indicators under defined conditions rather than definitive clinical outcome measures. This use case focuses on workflow integration, operational use, governance safeguards, and implementation lessons from AI-supported neuroimaging triage within a teleradiology model.

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Background

Stroke and head injury are leading contributors to death and long-term disability worldwide. In stroke care, the principle that delays in diagnosis may reduce the range of available interventions is widely recognised. Similarly, early detection of intracranial bleeding following trauma informs urgent referral and treatment pathways. Imaging, particularly non-contrast CT of the head, plays a central role in early assessment.

Artificial intelligence tools are increasingly being explored to support radiology workflows, particularly for triage, prioritisation, and structured detection support. This use case describes NeuralAssist, an AI-based image analysis tool integrated into a teleradiology reporting environment. In this implementation, AI is positioned as a decision-support and triage aid, not as an autonomous diagnostic system.

NeuralAssist Model Description

NeuralAssist is an AI-enabled clinical decision-support system designed to support radiologists in reviewing non-contrast CT (NCCT) head scans. The system combines multiple machine learning and deep learning components to identify imaging patterns associated with urgent neurological conditions. The model focuses on four categories of imaging indicators: Intracranial hemorrhage detection and quantification; shift detection; Dense MCA sign detection; and Skull fracture detection. The system combines neural network–based segmentation and detection models with rule-based post-processing steps intended to reduce false positives and support output consistency. Training datasets were derived from large, curated teleradiology image archives. Use of these datasets was conducted under institutional ethics committee approval.

AI outputs are presented as overlays, measurements, and probability indicators to support, not replace radiologist judgment.

Hemorrhage Detection and Quantification

A deep learning semantic segmentation framework is used to identify hemorrhagic regions at pixel-level resolution and supports multi-class detection of intracranial hemorrhage, including intraparenchymal (IPH), intraventricular (IVH), subarachnoid (SAH), subdural (SDH), and epidural (EDH) types. The processing pipeline includes artifact exclusion, scan series selection, Hounsfield Unit windowing, image normalization, and format standardization to ensure consistent input quality. Following segmentation, the system generates derived measurements such as dimensional estimates and categorical severity indicators. Internal validation testing has reported approximately 89% sensitivity and 91% specificity, with subtype classification accuracy above 90%; however, these figures are based on defined evaluation datasets and may vary across populations, scanner types, and acquisition protocols, and should therefore be interpreted as technical validation metrics rather than direct measures of clinical effectiveness.

Midline Shift Detection

A segmentation-based model is used to estimate midline position and measure displacement relative to a geometric reference derived from ventricular anatomy. Outputs include both visual overlays and numeric measurements in millimeters. Preprocessing includes exclusion of scans with severe artifacts or post-operative changes and standardized intensity normalization. A predefined displacement threshold is used to flag potential mass effect. Reported internal validation metrics include sensitivity of approximately 87% and specificity of approximately 88%. These results indicate supportive detection capability under evaluation conditions and require local validation before broader clinical reliance.

Dense MCA Detection

Detection of dense middle cerebral artery (MCA) sign, an early imaging marker sometimes associated with acute ischemic stroke is performed using a classical machine learning classifier based on intensity and asymmetry features. A Support Vector Machine model is used to support interpretability and stability. The system provides a binary present/absent flag with a confidence score to assist radiologist review. Reported internal validation metrics include sensitivity of approximately 87% and specificity of approximately 92%. This output is intended as a supportive indicator and not as a standalone diagnostic determination.

Skull Fracture Detection

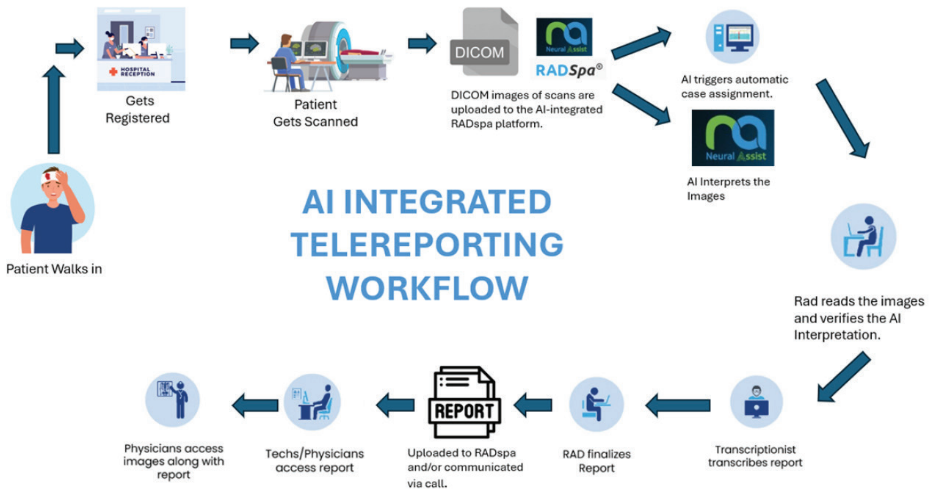
A multi-stage detection pipeline supports skull fracture identification. Components include deep learning–based detection, multi-class differentiation between fractures and sutures, ensemble slice-level decision logic, and post-processing for false-positive reduction. Preprocessing includes exclusion of pediatric scans and cases with major artifacts or post-operative alterations. Internal validation reports sensitivity near 90% and specificity near 93%, with fracture localization agreement around 90%. These measures describe algorithm performance under test conditions and may not generalize across all settings.

AI Integrated Telereporting Workflow

Neural Assist is integrated into a cloud-based teleradiology workflow platform (RADspa) that includes PACS and RIS functionality. DICOM images transmitted from participating hospitals are processed by the AI model prior to radiologist review.

AI outputs are used to support triage and prioritisation by flagging cases with imaging features that may indicate urgency. The system may generate structured preliminary annotations and draft text elements; however, final reports are issued only after radiologist validation. Radiologists review AI outputs alongside source images and retain full authority to accept, modify, or reject AI-generated findings. Reports are then transmitted back to referring hospitals through standard workflow channels, with critical findings communicated according to established clinical protocols. This workflow model positions AI as a prioritisation and workload-support layer, while preserving human clinical accountability.

Figure 01: AI-integrated teleradiology workflow.



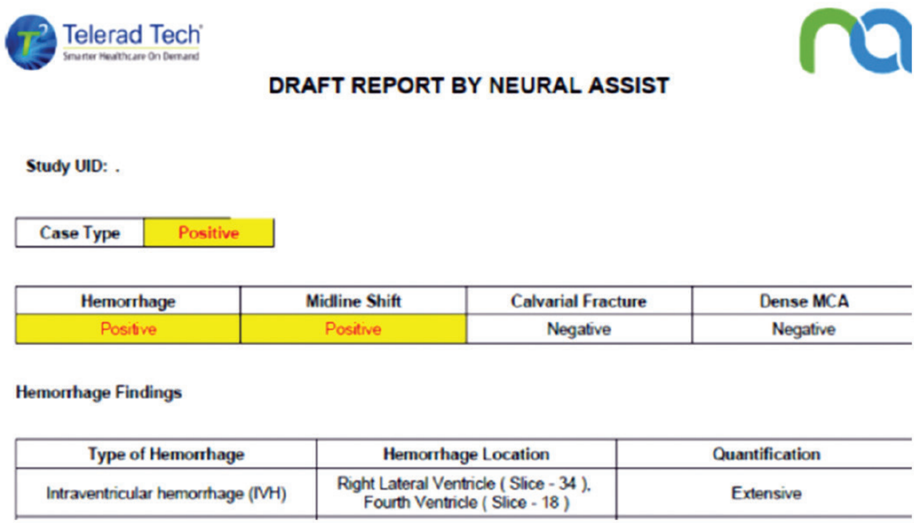
Case Examples

The following cases illustrate operational examples where AI outputs were compared with radiologist interpretations. These examples demonstrate concordance in selected cases but should not be interpreted as proof of universal performance.

Case 1.
Acute Multicompartmental Intracranial Hemorrhage with Significant Midline Shift

The patient had worsening confusion and a known history of subdural and subarachnoid hemorrhage. A non-contrast head CT was performed using helical axial acquisition with sagittal and coronal reformats, and iterative reconstruction techniques were applied to reduce radiation exposure (total exam DLP: 811 mGy/cm). The radiologist identified a 5.2 × 7.1 × 6.1 cm acute intraparenchymal hemorrhage in the right frontal lobe, a 0.5 cm subdural hemorrhage along the right frontoparietal convexity, and subarachnoid hemorrhages involving the bilateral frontal and temporal lobes, with associated intraventricular hemorrhage and a 1.8 cm leftward midline shift. Overall, the AI findings were concordant with the radiologist's report (Figure 2a–e).

Figure 02: (a) AI report and images showing (b and c) intraventricular IVH and subdural hemorrhage SDH, (d)intraparenchymal and intraventricular hemorrhage (IVH) (slice 18 and 34) and (e) subarachnoid hemorrhage (SAH) (slice 32)



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DRAFT REPORT BY NEURAL ASSIST

Study UID: .

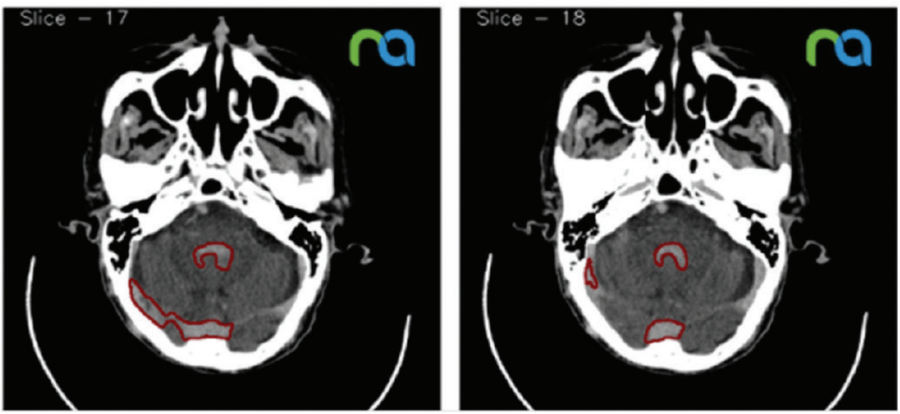
Case Type	Positive

Hemorrhage	Midline Shift	Calvarial Fracture	Dense MCA
Positive	Positive	Negative	Negative

Hemorrhage Findings

Type of Hemorrhage	Hemorrhage Location	Quantification
Intraventricular hemorrhage (IVH)	Right Lateral Ventricle (Slice - 34), Fourth Ventricle (Slice - 18)	Extensive

(a)



(b) (c)

(e)

(f)

Case 2. An acute nondisplaced fracture of the left occipital calvarium

The patient had a clinical history of a small post-traumatic subarachnoid hemorrhage in the right frontal lobe. A non-contrast CT (NCCT) scan of the head was performed with axial acquisition and sagittal and coronal reformats. The radiologist confirmed the presence of the small subarachnoid hemorrhage (not shown). The AI algorithm additionally flagged notice of an acute, nondisplaced fracture of the left occipital calvarium, which was subsequently confirmed on review (Figure 3a,b).

AI tool is integrated into a cloud teleradiology workflow to triage urgent head CT scans

Embedded directly in PACS/RIS enabled RADSpa platform for seamless workflow use

Figure 03: (a) AI report and (b) image showing left occipital bone fracture

Telerad Tech
Smarter Healthcare On Demand

DRAFT REPORT BY NEURAL ASSIST

Study UID:

Case Type	Positive

Hemorrhage	Midline Shift	Calvarial Fracture	Dense MCA
Suspicious	Negative	Positive	Positive

Calvarial Fracture Findings

Location	Slice No.
Left Occipital Bone Fracture	8

(a)

(b)

Provides visual overlays measurements and probability scores for radiologist review

Case 3. Stable multicompartmental acute Subdural Hemorrhage (SDH) with Right Parietal skull Bone Fracture

The patient had a history of head trauma and subdural hematoma. A non-contrast head CT (NCCT) was performed with axial acquisition and sagittal and coronal reformats. The radiologist identified an acute subdural hematoma along the right cerebral convexity and the anterior falx, along with a stable, acute nondisplaced fracture of the right frontoparietotemporal calvarium extending into the right mastoid region. The AI algorithm flagged the case as positive, with findings concordant with the radiologist's report (Figure 4a–f).

Figure 04: (a) AI report and (b, c) image showing subdural haematoma (SDH) along the right cerebral convexity and (d, e) acute nondisplaced fracture of the right parietal bone. Image (d) also shows a fracture mimic in the form of a skull suture (site of fusion).

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DRAFT REPORT BY NEURAL ASSIST

Study UID:

Case Type	Positive

Hemorrhage	Midline Shift	Calvarial Fracture	Dense MCA
Positive	Negative	Positive	Negative

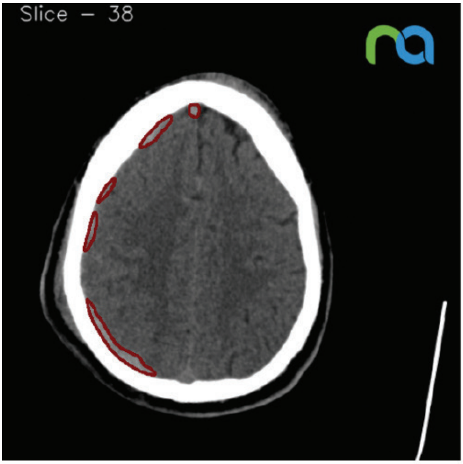
Hemorrhage Findings

Type of Hemorrhage	Hemorrhage Location	Quantification
Epidural Hematoma (EDH)/Subdural Hematoma (SDH)	Right Convexity (Slice - 38)	Thickness: 2 mm
Subdural Hematoma (SDH)	Right Convexity (Slice - 42)	Thickness: 5 mm
Subarachnoid Hemorrhage (SAH)	Right Convexity Sulci (Slice - 20)	Mild

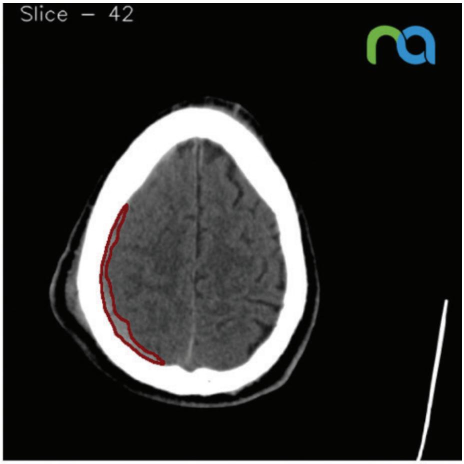
Calvarial Fracture Findings

Location	Slice No.
Right Parietal Bone Fracture	39
Right Temporal Bone Fracture	25

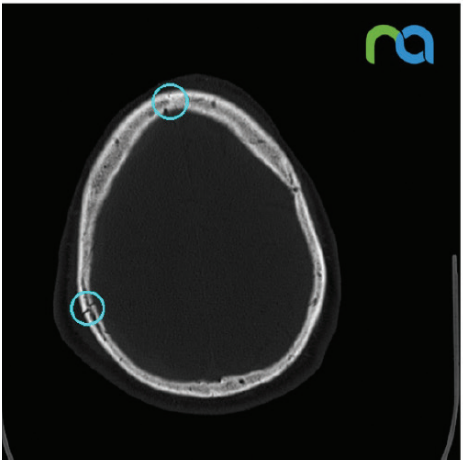
(a)



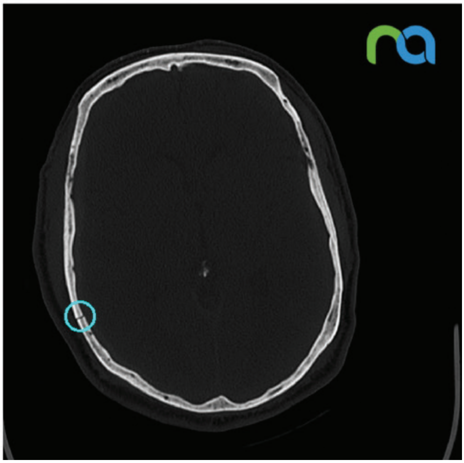
(b)



(c)



(d)



(e)

Ethics and Governance

Integration of Neural Assist into the reporting workflow was reviewed by an institutional ethics committee, with governance safeguards in place including mandatory human radiologist oversight for all final reports, use of AI strictly for triage and decision support rather than autonomous diagnosis or treatment decisions, maintenance of audit trails for AI outputs and report modifications, and implementation of data security and access controls within the PACS/RIS infrastructure. The cases used in the study were completely de-identified.

Challenges and Future Directions

Key implementation challenges include generalizability across imaging protocols and populations, interoperability with heterogeneous hospital IT systems, and the need for diverse multicenter training datasets. Broader validation across demographic and device variation remains important. Explainable AI approaches, clearer visualization tools, and user-centered interface design may improve interpretability and adoption. Integration with longitudinal imaging and clinical data systems may further support workflow value, subject to governance and privacy safeguards.

Conclusion

AI-supported neuroimaging triage tools can complement radiology workflows by highlighting potentially urgent findings and supporting prioritization within high-volume environments. NeuralAssist illustrates how combined deep learning and rule-based approaches can be embedded into teleradiology systems to support but not replace radiologist decision-making.

Observed technical performance metrics indicate supportive detection capability under defined validation conditions. Real-world clinical impact depends on workflow integration, human oversight, governance safeguards, and local validation. This model may inform future development of AI-supported emergency neuroimaging networks, particularly in settings seeking to extend specialist access through teleradiology infrastructure.

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