International Journal of Current Engineering and Technology
E-ISSN 2277 – 4106, P-ISSN 2347 – 5161
©2025 INPRESSCO®, All Rights Reserved
Available at http://inpressco.com/category/ijcet

Review Article

Advancements in CT Imaging for Neuro-Radiological Diagnosis: A Review of Techniques and Challenges

Dr. Sunita Dixit*

Professor Department of Computer Science & Engineering in St. Andrews Institute of Technology & Management, Gurgaon, India

Received 10 June 2025, Accepted 07 July 2025, Available online 08 July 2025, **Vol.15, No.4 (July/Aug 2025)**

Abstract

In neuro-radiological diagnosis, the imaging technology known as Computed Tomography (CT) has advanced significantly. Both traditional CT approaches and new techniques are encompassed in the advances. The fundamentals of CT imaging, such as X-ray attenuation, data collection, and image reconstruction (such as iterative reconstruction and Filtered Back Projection, or FBP), are crucial for its use as a tool. There are many types of CT scanners--axial, spiral, Multidetector CT (MDCT), and Cone Beam CT (CBCT)- each has different configurations and applications. The diagnosis of neurological disorders, such as stroke, traumatic brain injury, brain tumors, and congenital or degenerative diseases, makes extensive use of CT imaging. The recent advancements in CT technology (MDCT and now Dual-Energy CT (DECT) or Perfusion CT) have facilitated more accurate diagnoses and have provided a new methodology to determine functional status. The applications of artificial intelligence (AI) and machine learning (ML) in neuroimaging is gaining traction with several studies utilizing AI and ML to synthesize contrast-enhanced CT images, use multimodal neuro-imaging data to classify neurological disorders or optimize data and image reconstruction ability.

Keywords: *Computed Tomography, Neuro-Radiology, Artificial Intelligence, Machine Learning, Image Reconstruction, Neurological Disorders, MDCT, DECT, Perfusion CT*

Introduction

A complex and varied group of issues, neurological illnesses have a detrimental impact on people and put a great deal of strain on healthcare systems worldwide [1]. Whether in the realm of neurodegenerative diseases or urgent neurological emergencies, the demand for effective and creative therapies is significant. This introduction provides some context concerning current efforts in drug discovery and development in neurological disorders and the current pandemic of developments and research for insights and improvements in this field of rapid change.

CT has become a fundamental part of modern health care, particularly in the emergency medicine and neuro-radiology disciplines. It provides quick, non-invasive, and high-resolution pictures of internal structures, which have become essential for clinicians. CT is crucial for the early detection and management of life-threatening neurological disorders, especially stroke, traumatic brain injury, and intracranial haemorrhage [2].

The increase of CT machines in hospitals and emergency services has boosted doctors' ability to correctly diagnose and provide fast treatment, leading to improved patient outcomes. Over the past few decades, continuous innovations in CT technology have further solidified its place in routine healthcare practice, especially for brain imaging.

The severity of neurological diagnostic issues has decreased due to the advancement of contemporary technology that enhances the delivery of acute neurological treatment and the expanding dynamics. About 600 illnesses can affect the neurological system, according to a thorough analysis of medical records as well as literature. Alzheimer's, epilepsy, dementia, and cerebrovascular disease are some of these conditions. Included are stroke, multiple sclerosis, Neuro-infections, Parkinson's disease, brain tumors, and illnesses of the traumatic nervous system (including autism and brain trauma) [3][4].

MRI is the mainstay of imaging for neuroradiologists in their modern practice. In addition to enabling functional imaging techniques like perfusion, diffusion, as well as spectroscopy, it enables direct imaging of the feeding arteries and the whole brain. The ability of MRI to describe brain tissue is one of the reasons it has mostly replaced CT in clinical

*Corresponding author's ORCID ID: 0000-000-0000-0000
DOI: https://doi.org/10.14741/ijcet/v.15.4.3

routine imaging. In acute situations, such as neurotrauma, patients exhibiting symptoms of acute hemorrhage, and patients for whom MR imaging is contraindicated, CT is still the recommended imaging modality [5][6][7]. Nevertheless, CT indications are once again adjusting because of DECT, which made tissue characterization conceivable. Before CT, neuroimaging could only be done indirectly by looking at the brain. Common diagnostic options included traditional X-rays, myelography, pneumoencephalography and arteriography.

One of the most extensively studied areas of radiology nowadays is AI, which includes its subdivisions of ML as well as DL. Neuroradiology is among them. Findings from a recent PubMed database search for "artificial intelligence" and "neuroradiology" indicate that 2021 and 2022 had the highest number of articles. Neuroradiology really accounts for almost one-third of all radiology papers pertaining to AI. It looked at the material in the titles of all PubMed entries from this query beginning in 2017 and found that a rather significant number of DL papers deal with brain imaging, particularly imaging for stroke, which is a common issue [8][9]. AI can completely transform the medical imaging sector with more research and expanding industry capital investment, offering better patient outcomes, lower costs, more efficiency, as well as enhanced diagnostic accuracy [10]. Contrary to early predictions that AI will replace radiologists, a new paradigm has emerged recently that holds that AI would complement current radiologists and enable better, more effective patient care.

Structure of the Paper

This paper is structured to systematically review advancements in CT imaging for neuro-radiological diagnosis: Section I provides the introduction. Section II delves into the basic principles of CT imaging. Section III explores its clinical applications in diagnosing various neurological disorders. Section IV highlights recent technological advancements and challenges in CT. Section V investigates the use of ML and AI in medical images. Finally, Section VI presents the conclusion and outlines future work in the field.

Fundamentals of CT Imaging in Neuroradiology

CT imaging's speed, accessibility, and capacity to identify acute neurological disorders make it an essential tool in neuroradiology. CT creates cross-sectional pictures of the brain and spine using X-rays, allowing for rapid assessment of trauma, stroke, hemorrhage, tumors, and structural abnormalities. It is particularly useful in emergency situations because to its great sensitivity to bone and calcification [11][12]. Because CT scans are quicker and may be used in critical care settings, it is still the first-choice modality in acute situations even though. The contrast of soft tissues is improved by magnetic resonance imaging (MRI).

Basic Principles of CT Imaging

This section outlines the basic principles of CT imaging, beginning with X-ray attenuation, data acquisition from multiple projections, and the subsequent mathematical reconstruction of 2D images. It further explains Hounsfield Units for quantifying tissue density and classifies CT scanners based on their data acquisition methods, including axial, spiral, and cone-beam designs.

X-ray Attenuation Through an Object

Some photons are absorbed by the sample when X-rays go through it, while others make it to the detector. The formula for exponential attenuation describes the intensity of transmitted X-rays: $I = I_0 e^{-\mu x}$, where x is the material thickness, μ is the linear attenuation coefficient, and I_0 is the beginning intensity. The overall attenuation for numerous layers is $I_0 e^{-(\mu_1+\mu_2+\mu_3+\mu_4)x}$, as stated by the Lambert–Beer law. The observed intensity, representing the total of the attenuation coefficients along the X-ray path is thus proportional to the object's 2D transparency.

Computed Tomography Image Data Acquisition

An object is placed on a table, and an X-ray source rotates around it to create a CT image. The opposite side picks up X-rays passing through the object, and the data collection system receives these projections from various angles in order to rebuild tomographic images. A full scan normally needs 180°-360° of rotation, and the item must be motionless and included in all projections.

Computed Tomography Image Reconstruction

The mathematical technique of CT reconstruction uses 1D X-ray projections P (r, θ) captured around a 3D object from different angles to produce a 2D attenuation map f (x, y). These projections form a sinogram, representing line integrals at various angles. To reduce blurring from basic back projection, FBP applies a reconstruction kernel before back projection. The Fourier Slice Theorem, sometimes referred to as the Central Slice Theorem (CST), establishes a connection between the Radon transform and the 2D Fourier transform of an object. The final picture, f(x, y), is rebuilt from the frequency domain using F (u, v) and the inverse Fourier transform, as seen in Figure 1.

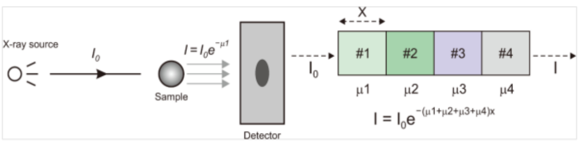

Fig.1 X-ray Beam Attenuation Model through Tissue Layers

Computed Tomography Numbers/Hounsfield Units

A CT picture is a digital matrix of pixels, with each pixel representing a voxel depending on its area and slice thickness. The size of each voxel is determined by the field of view, section thickness, as well as matrix size [13]. The tissue's linear attenuation coefficient is represented by pixel values, which are shown in greyscale, commonly using a 512×512 matrix with 12-bit depth. These figures are given in Hounsfield Units (HU), with air being -1000 HU and water being 0 HU. Acquisition methods are used to categories CT scanners: axial CT captures single slices with a fan beam, spiral CT enables continuous scanning, CBCT uses a conical beam for full-volume imaging, and MDCT employs a 2D detector array for fast, multi-slice acquisition. Figure 2 shown Reconstructing CT Images from Sinograms.

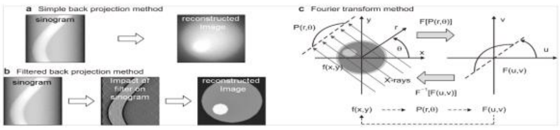

Fig.2 Methods for Reconstructing CT Images from Sinograms

General Classifications of Computed Tomography Scanners

CT scanners are classified by data acquisition method into traditional (axial), spiral (helical), and cone-beam CT (CBCT). Conventional CT successively acquires single-slice pictures using a fan-shaped X-ray beam [14]. Spiral CT allows for quicker, continuous scanning by moving the X-ray source as well as detectors in a helical route while the patient table moves forward. Conical X-ray beams are used in CBCT to scan greater volumes in a single rotation, primarily for radiation treatment.

Image Reconstruction Techniques

This section explores fundamental and advanced CT image reconstruction techniques, including Back Projection, the basis of FBP and Iterative Reconstruction (IR) techniques is the CST. These techniques are crucial for transforming raw CT data into clear, diagnostic images, with IR is especially well-known for reducing noise and artefacts in low-dose situations.

Back projection and Filtered Back projection (FBP)

As seen in Figure 3, the basic back projection method is smearing each projection back over the image space. While simple, it often results in blurred images due to the inherent smoothing of high-frequency components [15]. FBP enhances this by applying a filter (typically a ramp filter) to the projections before back projecting, thereby sharpening the image and improving resolution.

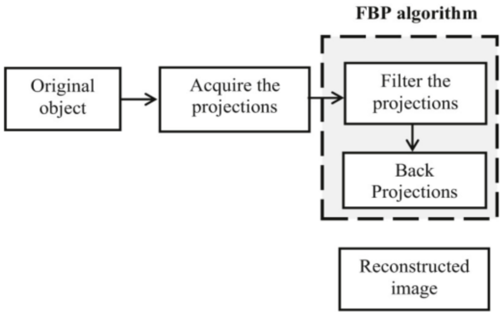

Fig.3 Filtered Back Projection

Central Slice Theorem (CST) and Fourier Transform

The Fourier Slice Theorem, often known as the CST, establishes a relationship between the center slice of the 2D Fourier transform of an object and the Fourier transform of a projection [16]. This principle underpins many reconstruction algorithms, including FBP, by enabling the transformation of projection data into frequency space for image reconstruction in Figure 4.

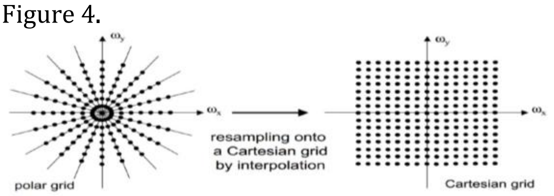

Fig.4 Central Slice Theorem

Iterative Reconstruction Methods:

IR methods approach image reconstruction Figure 5 by starting [17] with an initial guess and refining it through repeated iterations, combining data statistical characteristics as well as imaging system models [18][19]. These techniques can greatly lower artefacts and noise, particularly in low-dose imaging situations.

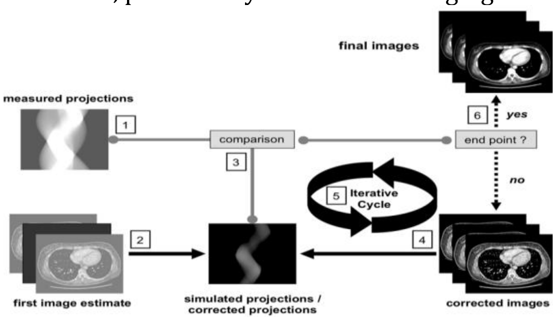

Fig.5 Iterative Cycle

CT Scanner Types and Configurations

CT scanners are classified based on their data acquisition method and X-ray beam geometry. The major types include:

Traditional (Axial) CT Scanners

A fan-shaped X-ray beam is used in traditional or axial CT scanners to acquire one slice of the object at a time.

The table stays still as During scanning; the X-ray source and detector rotate around the subject. The table gradually advances to the following location to obtain the next slice after each rotation [20]. While the step-and-shoot method delivers excellent results, it is very slow and inefficient for imaging dynamic or large objects. Axial CT is still a good option when static images are needed, and movement errors should be kept low.

Spiral (Helical) CT Scanners

Fast volumetric scans without any gaps between slices are possible with spiral or helical CT scanning because the X-ray tube and detector continually spin around the patient as the patient table goes steadily around the gantry. This results in the capture of data in a spiral route [21]. With a spiral CT scan, the patient does not need to hold still as long, and doctors can detect moving organs easily, avoiding artifacts. Both 3D images and dynamic imaging, such as perfusion, can be produced with this technology. The movement system in CT saves time on trauma imaging, scanning the heart, and whole-body exams than axial CT.

Multidetector CT (MDCT) Scanners:

An MDCT scanner combines many detector slices, so it is able to acquire several images at the same time as it scans. This allows imaging larger parts of the body quickly and gives very high-quality images that can be viewed from many positions or angles. The most common reason MDCT is used clinically is that it greatly reduces blurry images caused by patient movement and allows clear images of the brain and blood vessels. Since this scanner has many detector rows, it is possible to acquire very thin slices that increase accuracy and let tests be completed as rapidly as possible.

Cone Beam CT (CBCT) Scanners

CBCT devices collect a large dataset in a single revolution by using a cone-shaped X-ray beam and a piece of flat technology. CBCT is used often in dental X-rays, studies of dental bone structure, and radiation therapy as it has a high-resolution image and uses less radiation to view hard tissues than old CT machines. Since it can only see a narrow area and takes longer to create images, it isn’t used in all types of clinics [22]. Still, CBCT enables better planning and effective treatment for neuroradiology and oncology patients because of its 3D imaging.

Clinical Applications of CT in Neurological disorders

This section focuses on CT's application in the identification and management of certain neurological conditions. It is going to see how CT images help quickly diagnose disorders such as stroke and other brain blood vessel diseases, brain injuries, tumors and mass lesions, and conditions present right at birth or those related to aging [23]. Every subsection will talk about the key uses and benefits of CT in each of the given conditions.

Stroke and Cerebrovascular Imaging

CT is a crucial technique for the quick assessment of stroke patients, and it's especially crucial for determining if the stroke is ischaemic or haemorrhagic Non-contrast CT, as a rapid imaging tool, is frequently the first choice since it is easy to access (usually available in every emergency department) and exposes patients to very low risk, it typically can easily demonstrate intracerebral hemorrhages and later signs of ischemic stroke. CT studies and advances such as CTA (CT-angiography) and CTP (CT-perfusion) open a window into the cerebral circulation and blood flow that helps make timely recommendations for treating doctors, for example, to identify patients eligible for intravenous thrombolysis or thrombectomy. They help decide the level of artery blockage and brain tissue damage, which leads to the selection of the best treatment plan.

Traumatic Brain Injury (TBI)

CT scans are very sensitive to acute cranial hemorrhages, from acute subarachnoid, subdural, epidural, and intraparenchymal bleeding. CT scans are used to determine the amount of bleeding, the mass effect, and midline shift, which are all important considerations for surgical planning and prognosis. Follow-up imaging can show hematoma progression, as well as any complications [24][25]. Using certain CT scan imaging signals, one may forecast the likelihood of hematoma growth and patient outcomes.

Brain Tumors and Mass Lesions

The use of MRI is standard for evaluating brain tumors, but CT helps find calcifications, changes in the bone, and sudden bleeding in the tumor. It is particularly useful in emergency settings and for patients contraindicated for MRI. Contrast-enhanced CT scan delineates tumor margins and assess for mass effect or hydrocephalus. CT imaging is also valuable in surgical planning and in guiding biopsies.

Congenital and Degenerative Neurological Disorders

CT imaging aids in identifying structural anomalies associated with congenital disorders, such as hydrocephalus, agenesis of the corpus callosum, and craniosynostosis. In degenerative conditions like Alzheimer's disease, CT can reveal cerebral atrophy and ventricular enlargement [26]. MRI and nuclear medicine methods like PET and SPECT can detect earlier neurodegenerative changes with a greater sensitivity; however, CT may be particularly useful in settings where MRI is not available or cannot be performed.

Recent Technological Advancements and challenges in CT

Recent developments in CT technology have improved the diagnostic potential of CT, providing for higher resolution imaging, faster acquisition times, and more advanced tissue characterization. Innovations such as MDCT, DECT, and CTP have created new clinical abilities for CT in the fields of cardiology, oncology, neurology, and emergency medicine. Thus, these advances pose new challenges in terms of radiation dose, data processing, and clinical integration [27].

Multi-Detector CT (MDCT)

MDCT has revolutionized CT imaging by using multiple rows of detectors to simultaneously acquire multiple slices of data, allowing for fast scans and improved spatial resolution. The introduction of quick scans enabled the imaging of the whole heart within a single breath-hold, improving the risk of motion artifacts, and CT angiography provides evaluation of vessel detail [28]. Nonetheless, along with the benefits are challenges that include an increased risk of radiation exposure if not well managed, becomes fast data generation in such large quantities that it requires significant capacity for storage and processing, and it requires highly trained personnel to appropriately phase and extract the complex images of the heart and vasculature from the data generated.

Dual-Energy CT (DECT)

DECT uses two different energy spectra to provide material-specific imaging, which will improve tissue differentiation, including identifying uric acid versus calcium stones along with superior tumor detection and characterization in oncology, and rapid identification of hemorrhage and edema in emergency settings. However, DECT has limitations, including more complicated and expensive systems, a need for sophisticated software tools to identify precise material decomposition, and limited use in general clinical practice, due in large part to specialized training and complexity and availability of infrastructure.

Perfusion CT and Functional Imaging

CTP images tissue blood flow and viability dynamically, providing potential benefits in the clinic, including greater identification and treatment planning for acute stroke by assessing the ischemic penumbra, myocardial perfusion assessment of patients with cardiology conditions, and functional tumor characterization and assessment of therapy response in oncology. However, this technology also brings several limitations, including cumulative radiation exposure while performing multiple sequential scans, the potential for patient movement or physiological movement and the resulting artifacts impacting reconstruction and analysis of imaging quality, and the ability to analyze the perfusion CT findings quantitatively, including accurate calibration and expert-level interpretation.

Literature Review

This literature review provides an overview of the most recent studies on using AI and ML in medical imaging. It points to different innovative ways used in various technologies for better identification, synthesis, and reconstruction of images.

Pham, Kitamura and Tsunoyama (2025) examine fuzzy logic-based nonlinear dynamical features extracted from CT data of extravasation to represent the trauma cases to find radiographic patterns, so that these patterns may help with clinical prediction and clinical intervention. The spatial and temporal analysis of extravasation imaging is described from three trauma cases. Using geo-statistics and nonlinear dynamics, this study aims to identify subtle, dynamic patterns that can enhance real-time detection and prediction of complications. These findings offer a foundation for integrating advanced imaging analytics into trauma care, improving decision-making, and optimizing patient outcomes through early intervention[29].

Rokham, Falakshahi and Calhoun (2024) they incorporated deep convolutional frameworks and bagging approaches for diagnostic classification, identifying potential biomarkers and mitigating the effects of label noise across mood and psychosis categories using structural and functional MRI data. They trained separate base models on various data subsets using repeated k-fold cross-validation procedures, then combined independent models for the final classification. Moreover, they interpreted the results and identified class-specific relevant learned features contributing to a successful diagnosis and highlighted differences for different modalities. Overall, their proposed method shows improvement in classification performance [30].

Charatpangoon et al. (2024) an ML method using a denoising autoencoder to remove the noise resulting from dose reduction. The study was conducted using CTP images from the PRove-IT dataset with 46 acute ischemic stroke patients. Two kinds of noise were added to approximate low-dose images: Gaussian noise and Poisson noise, for different reduction levels. The findings indicate that by reducing the dose to 80%, the original and denoised images were almost identical, Gaussian and Poisson noises have average Structural Similarity Indexes of 0.959 as well as 0.925, respectively. Some of the CTP maps had scores lower than TCD maps, but they could distinguish the tissue at risk and the clear infarction, with average Gaussian and

Poisson SSIM scores of 0.942 and 0.910 respectively. The study found out that it is possible to reduce radiation in CTP scans by about 80% and still retain good quality in the scans [31].

Yang et al. (2023) provide a spatial attention-guided generative adversarial network (SAG-GAN) that can immediately generate CE-CT pictures that match the NC-CT images of the patient. They present a spatial attention-guided generator for SAG-GAN that uses a lightweight spatial attention module to highlight the regions of NC-CT images relevant to the synthesis task and disregard irrelevant regions. They evaluate the effectiveness of their method on two tasks: creating arterial phase as well as portal venous phase CE-CT image synthesis. Analytical and qualitative findings show that SAG-GAN outperforms current GAN-based picture generation techniques [32].

Interiano, Palma and Leiva (2023) implemented a quantitative methodology aimed at discovering new things and was structured as an experiment. The approach used was iterative, with four stages. First, they tested and fine-tuned the EfficientNetV2B0, MobileNetV3-Small, as well as MobileNetV3-Large models. This second iteration included testing and fine-tuning of the InceptionResNetV2, EfficientNetV2B1, and EfficientNetV2B2 models. The third update included the creation of a database including medical photographs of patients from Honduras. Predictions were made in the fourth utilizing the models that performed the best. It was discovered that the evaluated models had achieved an average accuracy of 98.01% in the first increment and 98.01% in the second. It was feasible to secure the creation of a local database for future research lines and assess the classification system using predictions of radiographic images of patients in Honduras [33].

Sheikhjafari et al. (2022) A diffeomorphic deformable registration is the basis of the left ventricle may be distinguished from 2D and 3D pictures or volumes using a novel end-to-end supervised cardiac MRI segmentation technique. The methodology parameterizes the transformation to replicate the actual heart deformation by calculating radial and rotational components using a DL approach. The method showed significant improvements over prior learning and non-learning-based methods in terms of the Dice score and Hausdorff distance metrics when evaluated on three different data sets [34].

Table I provides a summary of recent studies on AI and ML applications in medical imaging, detailing their respective approaches, key findings, challenges, and future directions.

Table 1 Comparative summary of Recent Imaging and Diagnostic Methodologies

Reference	Study On	Approach	Key Findings	Challenges / Limitations	Future Directions
Pham, Kitamura, Tsunoyama (2025)	CT imaging of extravasation in trauma cases	Fuzzy logic, nonlinear dynamics, geostatistics	Detected subtle, dynamic radiographic patterns aiding real-time prediction of complications	Limited to three trauma cases; generalizability needs validation	Integration of imaging analytics into real-time trauma care for predictive intervention
Charatpangoon et al. (2024)	Low-dose CT Perfusion for stroke	Denoising Autoencoder (DAE)	Achieved 80% dose reduction with high SSIM; retained infarction and penumbra detection	SSIM drop in CTP maps; only Gaussian and Poisson noise types tested	Real-world validation and generalization to broader noise profiles
Rokham, Falakshahi, Calhoun (2024)	Diagnostic classification in mood and psychosis using MRI	Deep CNNs, bagging ensemble, repeated k-fold CV	Identified biomarkers and improved classification by mitigating label noise	Interpretation of deep features across modalities remains complex	Further development of multimodal, noise-robust diagnostic models
Yang et al. (2023)	CE-CT image synthesis from NC-CT	SAG-GAN with spatial attention module	High-quality synthesis of arterial and portal venous phase CE-CT images	Limited to specific contrast phases and datasets	Generalization to other imaging modalities and broader clinical deployment
Andrews Interiano et al. (2023)	Classification of medical images from Honduran patients	MobileNetV3, EfficientNetV2, InceptionResNetV2 in iterative design	Achieved up to 98.01% accuracy, built local medical image database	Limited sample diversity; focus was local/regional	Expand dataset for broader validation and apply models in real-world diagnostics
Sheikhjafari et al. (2022)	Left ventricle segmentation in cardiac MRI	DL+ diffeomorphic deformable registration	Outperformed learning and non-learning methods on Dice & Hausdorff metrics	High computational demands; parameter tuning	Extend to other heart structures and real-time implementation

Conclusion And Future Work

CT imaging has firmly established itself as an indispensable tool in neuro-radiological diagnosis, driven by ongoing advancements in its fundamental principles and technological applications. This review has elucidated the critical aspects of CT, ranging from basic X-ray attenuation and image reconstruction methods like FBP and iterative techniques, to the diverse classifications of CT scanners, including axial, spiral, MDCT, and CBCT. The rapid pace of non-invasive, high-resolution imaging with CT makes it critical to the diagnosis and management of several neurological conditions, such as stroke, traumatic brain damage, brain tumors, congenital conditions, and degenerative diseases. Significant advancements in technology, such as MDCT, DECT, and Perfusion CT, have improved diagnostic performance and functional assessment in terms of vascular assessment and tissue viability for timely therapeutic interventions. In addition, the rapid integration of AI and ML into the field of neuroimaging is on the verge of changing the way care is provided to patients, from producing contrast-enhanced images to higher levels of diagnostic classification and image optimization. As advanced CT imaging technology and AI become more established as the standards of care, radiologists will have even more beneficial capabilities for delivering quality and efficient patient care.

Future developments in neuro-radiological CT imaging will be centered on improved decision-making in real-time using AI and ML systems, as well as a smooth transition between digital twin technology and IoT integration for industrial system optimization. A fundamental component of iterations is IR methods, which are necessary to further minimize noise and key artefacts in low-dose imaging modalities. The aim of maintaining a robust model with AI for automated image interpretation and subsequently disease classification remains a primary goal in this domain. In addition, ensuring clinical workflows are robustly validated concerning any new CT technology as well as AI technology before clinical use, and evaluating ethical concerns surrounding data privacy and algorithmic bias, represent the key challenges moving forward.

References

[1] F. Raza, “Neurological Disorders: A Comprehensive Review of Insights and Innovations in Treatment Development,” Unique Endeavor Bus. Soc. Sci., vol. 2, no. 1, pp. 28–36, 2024.

[2] S. B. Shah, “Artificial Intelligence (AI) for Brain Tumor Detection: Automating MRI Image Analysis for Enhanced Accuracy,” Int. J. Curr. Eng. Technol., vol. 14, no. 06, pp. 320–327, Dec. 2024, doi: 10.14741/ijcet/v.14.5.5.

[3] S. Aljahdali, G. Azim, W. Zabani, S. Bafaraj, J. Alyami, and A. Abduljabbar, “Effectiveness of radiology modalities in diagnosing and characterizing brain disorders,” Neurosciences (Riyadh)., vol. 29, no. 1, pp. 37–43, 2024, doi: 10.17712/nsj.2024.1.20230048.

[4] R. Dattangire, D. Biradar, and A. Joon, “AI-Enhanced U-Net for Accurate Low-Grade Glioma Segmentation in Brain MRI: Transforming Healthcare Imaging,” in 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), IEEE, Jul. 2024, pp. 1–6. doi: 10.1109/ICEEICT61591.2024.10718440.

[5] A. A. Postma, M. Das, A. A. R. Stadler, and J. E. Wildberger, “Dual-Energy CT: What the Neuroradiologist Should Know,” Curr. Radiol. Rep., vol. 3, no. 5, pp. 1–16, May 2015, doi: 10.1007/s40134-015-0097-9.

[6] R. P. Mahajan, “Transfer Learning for MRI image reconstruction: Enhancing model performance with pretrained networks,” Int. J. Sci. Res. Arch., vol. 15, no. 1, pp. 298–309, Apr. 2025, doi: 10.30574/ijsra.2025.15.1.0939.

[7] V. Kolluri, “Revolutionizing healthcare delivery: The role of AI and machine learning in personalized medicine and predictive analytics,” Well Test. J., vol. 33, no. 2, pp. 591–618, 2024.

[8] D. T. Wagner et al., “Artificial Intelligence in Neuroradiology: A Review of Current Topics and Competition Challenges,” Diagnostics, vol. 13, no. 16, Aug. 2023, doi: 10.3390/diagnostics13162670.

[9] S. R. Sagili, S. Chidambaranathan, N. Nallametti, H. M. Bodele, L. Raja, and P. G. Gayathri, “NeuroPCA: Enhancing Alzheimer’s disorder Disease Detection through Optimized Feature Reduction and Machine Learning,” in 2024 Third International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), IEEE, Jul. 2024, pp. 1–9. doi: 10.1109/ICEEICT61591.2024.10718628.

[10] S. Pahune and N. Rewatkar, “Large Language Models and Generative AI’ s Expanding Role in Healthcare Large Language Models and Generative AI’ s Expanding Role in Healthcare,” Int. J. Res. Appl. Sci. Eng. Technol., vol. 11, no. 8, pp. 1–14, 2024, doi: 10.13140/RG.2.2.20109.72168.

[11] O. Rapalino, “Fundamentals of Neuroradiological Imaging,” in Textbook of Neurointensive Care, Cham: Springer International Publishing, 2024, pp. 39–49. doi: 10.1007/978-3-031-62220-5_3.

[12] S. Singamsetty, “Neurofusion: Advancing Alzheimer’s Diagnosis with Deep Learning and Multimodal Feature Integration,” Int. J. Educ. Appl. Sci. Res., vol. 8, no. 1, pp. 23–32, 2021, doi: 10.5281/14889013.

[13] N. Patel, “Quantum Cryptography In Healthcare Information Systems: Enhancing Security In Medical Data Storage And Communication,” J. Emerg. Technol. Innov. Res., vol. 9, no. 8, pp. 193–202, 2022.

[14] H. Zainab, A. R. A. Khan, M. I. Khan, and A. Arif, “Ethical Considerations and Data Privacy Challenges in AI-Powered Healthcare Solutions for Cancer and Cardiovascular Diseases,” Glob. Trends Sci. Technol., vol. 1, no. 1, pp. 63–74, 2025.

[15] R. Schofield et al., “Image reconstruction: Part 1 – understanding filtered back projection, noise and image acquisition,” J. Cardiovasc. Comput. Tomogr., vol. 14, no. 3, pp. 219–225, May 2020, doi: 10.1016/j.jcct.2019.04.008.

[16] A. V. Narasimhadhan, A. Sharma, and D. Mistry, “Image Reconstruction from Fan-Beam Projections without Back-Projection Weight in a 2-D Dynamic CT: Compensation of Time-Dependent Rotational, Uniform Scaling and Translational Deformations,” Open J. Med. Imaging, vol. 03, no. 04, pp. 136–143, 2013, doi: 10.4236/ojmi.2013.34021.

[17] L. L. Geyer et al., “State of the Art: Iterative CT Reconstruction Techniques,” Radiology, vol. 276, no. 2, pp. 339–357, Aug. 2015, doi: 10.1148/radiol.2015132766.

[18] M. Beister, D. Kolditz, and W. A. Kalender, “Iterative reconstruction methods in X-ray CT,” Phys. Medica, vol. 28, no. 2, pp. 94–108, Apr. 2012, doi: 10.1016/j.ejmp.2012.01.003.

[19] A. Balasubramanian and N. Gurushankar, “Hardware-Enabled AI for Predictive Analytics in the Pharmaceutical Industry,” Int. J. Lead. Res. Publ., vol. 4, no. 1, pp. 1–13, 2025, doi: 10.5281/zenodo.14673310.

[20] J. Hsieh, Computed Tomography, Second Edition. 1000 20th Street, Bellingham, WA 98227-0010 USA: SPIE, 2009. doi: 10.1117/3.817303.

[21] V. Kolluri, "Machine Learning Applications in Medical Imaging: The Advancements And Challenges of Using Machine Learning to Interpret Medical Images," SSRN Electron. J., vol. 9, no. 2, pp. 919–922, 2022.
[22] H. Zainab, A. R. A. Khan, M. I. Khan, and A. Arif, "Innovative AI Solutions for Mental Health : Bridging Detection and Therapy," Glob. J. Emerg. AI Comput., vol. 1, no. 1, pp. 51–58, 2025.
[23] S. Singamsetty, "Lightweight Reg Net-Driven Deep Learning Framework for Enhanced Classification of Neurodegenerative Diseases from MRI Images," Int. J. Adv. Eng. Sci. Res., vol. 10, no. 1, pp. 28–37, 2023, doi: 10.5281/zenodo.15034011.
[24] A. Hillal, T. Ullberg, B. Ramgren, and J. Wassélius, "Computed tomography in acute intracerebral hemorrhage: neuroimaging predictors of hematoma expansion and outcome," Insights Imaging, vol. 13, no. 1, pp. 1–16, Nov. 2022, doi: 10.1186/s13244-022-01309-1.
[25] R. P. Mahajan, "Development of Predictive Models for Early Detection of Alzheimer ' s Disease Using Machine Learning," Int. J. Curr. Eng. Technol., vol. 15, no. 2, pp. 115–123, 2025.
[26] S. Siuly and Y. Zhang, "Medical Big Data: Neurological Diseases Diagnosis Through Medical Data Analysis," Data Sci. Eng., vol. 1, no. 2, pp. 54–64, Jun. 2016, doi: 10.1007/s41019-016-0011-3.
[27] A. S. Lowe and C. L. Kay, "Recent developments in CT: a review of the clinical applications and advantages of multidetector computed tomography," Imaging, vol. 18, no. 2, pp. 62–67, Jun. 2006, doi: 10.1259/imaging/96702094.
[28] S. Pandya, "Predictive Modeling for Cancer Detection Based on Machine Learning Algorithms and AI in the Healthcare Sector," TIJER - Int. Res. J., vol. 11, no. 12, pp. 549–555, 2024.
[29] T. D. Pham, M. Kitamura, and T. Tsunoyama, "Recurrence Dynamics of Extravasation on Computed Tomography," in 2025 IEEE International Conference on Cybernetics and Innovations (ICCI), 2025, pp. 1–6. doi: 10.1109/ICCI64209.2025.10987383.
[30] H. Rokham, H. Falakshahi, and V. D. Calhoun, "Label Noise-Robust Ensemble Deep Multimodal Framework For Neuroimaging Data," in 2024 46th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), 2024, pp. 1–4. doi: 10.1109/EMBC53108.2024.10782672.
[31] P. Charatpangoon et al., "Radiation Dose Reduction in Computed Tomography Perfusion of Acute Ischemic Stroke Patients Using a Denoising Autoencoder," in 2024 IEEE International Symposium on Biomedical Imaging (ISBI), 2024, pp. 1–5. doi: 10.1109/ISBI56570.2024.10635381.
[32] Y. Yang et al., "Spatial Attention-Guided Generative Adversarial Network for Synthesizing Contrast-enhanced Computed Tomography Images," in 2023 45th Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), IEEE, Jul. 2023, pp. 1–4. doi: 10.1109/EMBC40787.2023.10340586.
[33] A. A. A. Interiano, M. A. M. Palma, and K. M. R. Leiva, "Prediction of Spinal Abnormalities in Neuroradiology Images Applying Deep Transfer Learning," in 2023 IEEE International Conference on Machine Learning and Applied Network Technologies (ICMLANT), IEEE, Dec. 2023, pp. 1–7. doi: 10.1109/ICMLANT59547.2023.10372991.
[34] A. Sheikhjafari, D. Krishnaswamy, M. Noga, N. Ray, and K. Punithakumar, "Deep Learning Based Parametrization of Diffeomorphic Image Registration for the Application of Cardiac Image Segmentation," in 2022 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), IEEE, Dec. 2022, pp. 1164–1169. doi: 10.1109/BIBM55620.2022.9994849.