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CT Scan Image Denoising and Exposure Optimization Using Cascaded U-Net with Sparse Constraints

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Abstract:- Accurate diagnoses in medical imaging heavily rely on high-quality 2D image slices from CT scans This study proposes a novel, data-driven pipeline to optimize these slices for improved diagnostic accuracy. The pipeline integrates patient information with CT data acquisition, enabling personalized scan settings for each patient. An ARIMA time series model optimizes exposure time, balancing the need for high-quality images with minimizing radiation dose.Following data acquisition, the pipeline employs a cascaded network for pre-processing. This network meticulously removes noise and artifacts that can obscure anatomical details. Subsequently, a super-resolution model leveraging SRGAN and DENSE-Net enhances image resolution and sharpens intricate structures within the scanned area.The proposed methodology is rigorously evaluated on a dataset encompassing CT scans from 299 patients. This comprehensive analysis compares the quality of images generated by the pipeline against those produced by traditional methods. The study focuses on key metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) to assess improvements in image quality.This data-driven framework has the potential to significantly improve diagnostic accuracy in medical imaging. By providing clearer and more detailed images, healthcare professionals can make more informed decisions regarding treatment plans, ultimately leading to better patient outcomes.

Keywords*:* Cascaded Residual Dense U-net (RDU-Net) with Sparse Auto Encoder (SAE), CT scan, 2D Image Slices, Super Resolution Model, Autoregressive Integrated Moving Average (ARMIA),Structural Similarity Index (SSI), Peek Signal to Noise Ratio (PSNR),optimal exposure time, Deep Denoising, Hybrid Network Architecture..

1. Introduction:-

In the field of modern healthcare, accurate diagnosis and effective treatment planning depend on the quality of medical imaging. Computed tomography (CT) scans, renowned for their detailed cross-sectional views of internal structures, are of great value in detecting diseases, evaluating injuries, and monitoring the progress of treatment [1]. However, the intrinsic noise of CT scans, arising from factors such as electronic sensors, radiation scatter, and patient motion, poses a significant challenge to accurate interpretation and diagnosis.This noise manifests as blurred and reduced image contrast, obscuring complex anatomical features and hindering the detection of subtle abnormalities. This presents a serious challenge for radiologists and medical specialists, potentially leading to misdiagnosis and suboptimal treatment plans [4].

Effectively addressing this noise challenge is critical to maximizing the potential of CT scans in healthcare. While various denoising techniques have been developed, they often fall short due to limitations in effectiveness, interpretability, or computational feasibility [2]. This research aims to bridge this gap by proposing a groundbreaking approach that not only bypasses CT scans but also optimizes exposure time, paving the way for better diagnostic accuracy, reduced radiation dose and, ultimately, better patient care.This research proposes a groundbreaking approach that uses a cascaded RDU-Net and sparse auto encoder to remove noise and artifacts from CT image slices, providing unparalleled image clarity for accurate diagnosis [3]. Also, use a time series model based on the ARIMA technique to predict the optimal exposure time for each individual patient, ensuring high-quality images while minimizing radiation exposure.

2. Literature Review:-

Accurate diagnoses in medical imaging rely heavily on high-quality 2D image slices derived from CT scans. However, limitations exist in traditional image acquisition and processing techniques [7]. This challenge has motivated the exploration of advanced image processing methodologies to enhance CT scan image quality. Recent research has demonstrated the promising potential of deep learning techniques in medical image processing tasks.[1]The paper proposed by Gurrola-Ramos et al. exploresits potential for our CT scan image denoising project,The innovative RDU-Net, unlike traditional U-Net architectures, uses densely connected convolutional layers for efficient feature reuse and robust extraction. Its hierarchical structure with residual density units (RDUs) enables both local and global residual learning, tackles the vanishing gradient problem, and efficiently predicts noise residuals. This noise-agnostic approach seamlessly adapts to different noise levels, making it ideal for real-world scenarios [6].

Continuing the exploration of this topic, a systematic review conducted by Shengqin et al. merges the power of deep convolutional networks (DCNs) and sparse representation theory to effectively separate image features from noise, leading to significant improvements in denoising performance.[2]At the heart of the proposed algorithm lies a unique blend of techniques. Deep convolution layers, the workhorses of modern image processing, extract and learn complex features from noisy images. This learning is further guided by prior and sparse representation theory, which leverages the natural sparsity of images to identify and suppress noise artifacts. To achieve efficient noise separation, the algorithm employs an end-to-end network architecture. This network, built with dilated convolutional and fully connected layers, acts like a multi-stage filter, progressively refining the image information while discarding noise components [10].

This paper by Heinrich et al. addresses the significant challenge of preserving image quality in low-dose CT scans, where reduced radiation exposure introduces quantum noise [3].The authors propose two convolutional neural network (CNN) architectures specifically designed for low-dose CT denoising: Res-FCN and ResU-Net.Res-FCN employs a fully-convolutional architecture with 5x5 filter blocks, while ResU-Net leverages a modified U-Net structure featuring 10 convolutional blocks arranged in a multi-scale fashion.Both architectures incorporate a crucial element – residual connections, which enable gradients to flow directly through the network, facilitating learning and enhancing denoising performance.

Building on these insights, all of metal. Present a comprehensive overview of Medical Image Denoising with Recurrent Residual U-Net (R2U-Net) base Auto-Encoder. [4] the authors present two novel deep learning models: RU-Net and R2U-Net. Both models build on the foundation of U-Net, a widely adopted architecture for medical image segmentation. However, they include additional components to increase performance in noisy environments. RU-Net takes advantage of Recurrent Convolutional Neural Networks (RCNNs), while R2U-Net takes it a step further by integrating Recurrent Residual Convolutional Layers (RRCNNs).

Lastly, Schaffer et al. offers valuable insights into utilizing ARIMA models for population-level assessments, making it relevant to our project on CT scan image denoising and exposure optimization. [5]The paper delves into the application of ARIMA models to assess health policy interventions, outlining key aspects like modeling impact shapes, model selection, transfer functions, and interpretation. Furthermore, it provides a practical example illustrating the use of ARIMA in analyzing the impact of a policy change on medication prescription.

3. Proposed Methodology:-

This proposed approach to CT scan image denoising leverages a multi-pronged strategy, combining deep learning and statistical modeling for optimal results. At the core lies a cascaded RDU-Net architecture, utilizing multiple Residual Dense U-Net modules in sequence to progressively refine denoising. This is further enhanced by a sparse autoencoder, which learns efficient feature representations from noisy images. Importantly, exposure optimization is achieved through an ARIMA model, analyzing historical data to personalize radiation settings for each patient, balancing image quality with safety [9].

The workflow begins with capturing 2D slices using a CT scanner, where exposure time is optimized by the ARIMAX model. Preprocessing steps refine these slices further, followed by the cascaded network. The sparse autoencoder extracts key features, and RDU-Net progressively denoises the images. Super-resolution models like SRGAN and DENSE-Net further enhance image quality. Throughout the process, image quality metrics and noise characteristics are monitored to ensure diagnostic suitability. Finally, the enhanced 2D slices are reconstructed into high-quality 3D images.

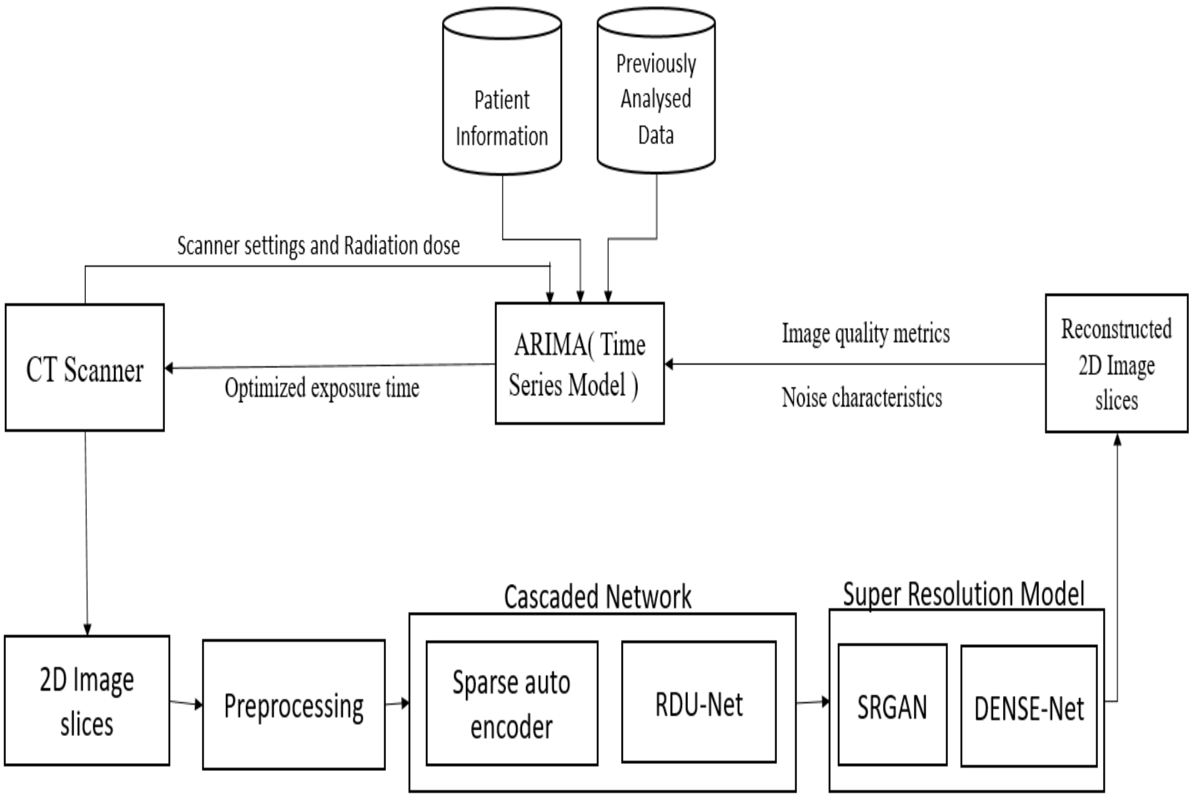


Fig.1 Proposed System

The RDU-Net, building upon the U-Net architecture, boasts dense connections and residual blocks for enhanced feature extraction. Its encoder delves into the noisy image, progressively down sampling to capture hierarchical features. Dense connections within this stage ensure efficient information flow during training. Each residual block, utilizing multiple convolutional layers, learns both low-level and high-level features with the crucial help of residual connections preserving the original information. These features are further enhanced by dense connections within the block. Once extracted, the decoder up samples them back to the original size, meticulously reconstructing the denoised image by fusing features from various scales. Dense connections here play a vital role in recovering fine details.

However, the RDU-Net doesn't work alone. The sparse autoencoder steps in with its unique talent for compact feature representation. Its encoder learns to identify meaningful features from the noisy input, guided by a sparsity constraint that encourages discarding irrelevant information. These essential features are compressed into a compact form in the bottleneck layer. The decoder then takes over, reconstructing the image from this sparse representation, aiming to minimize the difference from the original noisy input.

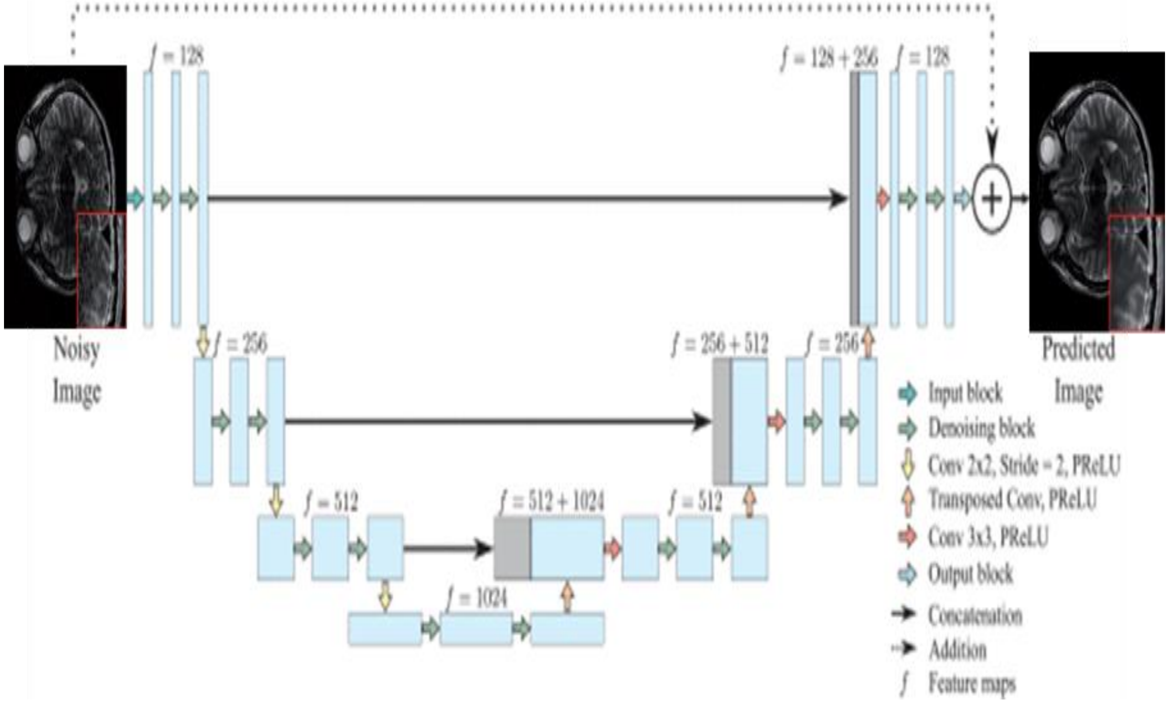


Fig.2 Architecture of RDU-Net Model

These two architectures work in close collaboration. The sparse autoencoder preps the ground by providing the RDU-Net with valuable, noise-filtered features. The RDU-Net, in turn, refines these features further, ultimately delivering a denoised image of superior quality.

Where:- $$\widehat{X} = \arg\min_{X} \frac{\varphi}{2}\|X - Y\|_2^2 + \frac{1}{2}\sum_{i}\|D\alpha_i - A_i X\|_2^2$$

X^is the estimated Image

X is the noise Image

Y is the counterparts

Ψ represents the Lagrange multiplier

D is the DCT dictionary set tailored to x

α is a non zero sparse vector with sparsity

Before unleashing this duo on real data, some preprocessing might be necessary to remove artifacts and enhance contrast. The images then travel through the cascaded RDU-Net, learning global and local features, while the autoencoder simultaneously extracts its meaningful subset. This joint learning process ensures both architectures contribute optimally to the final denoised image

The journey doesn't end there. The success of this approach is validated through evaluation using established image quality metrics like PSNR and SSIM. Fine-tuning of hyperparameters becomes crucial to squeeze out the best possible denoising results.

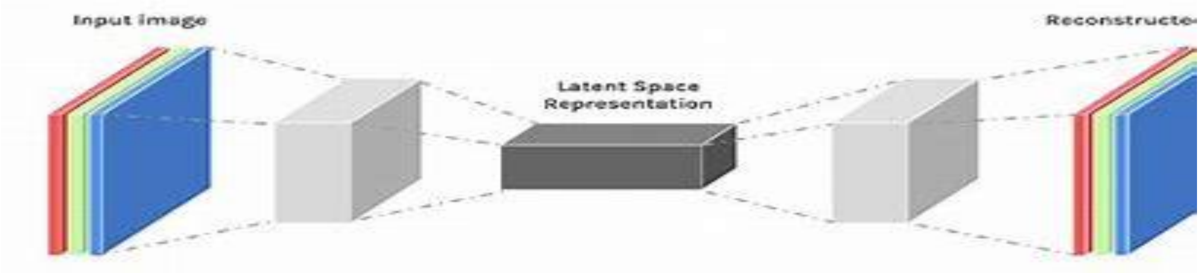


Fig.3 Architecture of Sparse Auto Encoder

Super Resolution Model:

The integrated approach for enhancing the quality of CT scan images involves a two-step process, employing the Super-Resolution Generative Adversarial Network (SRGAN) and DenseNet. SRGAN focuses on elevating image resolution, specifically targeting low-resolution input. In the first step, the generator, implemented as DenseNet, takes the denoised CT scan image output from the cascaded RDU-Net and sparse autoencoder as input. Recognized for its dense connections, DenseNet facilitates improved feature reuse and gradient flow, enabling the generator to map low-resolution inputs to high-resolution outputs.

In practice, the denoised CT scan image undergoes processing through DenseNet, acting as the generator in SRGAN. Dense connections within the architecture aid in capturing fine details, contributing to the generation of high-quality, denoised, and super-resolved CT scan images. This combined SRGAN-DenseNet approach ensures the delivery of images that not only possess enhanced resolution but also retain critical diagnostic information, ultimately contributing to improved clinical outcomes in medical imaging applications.

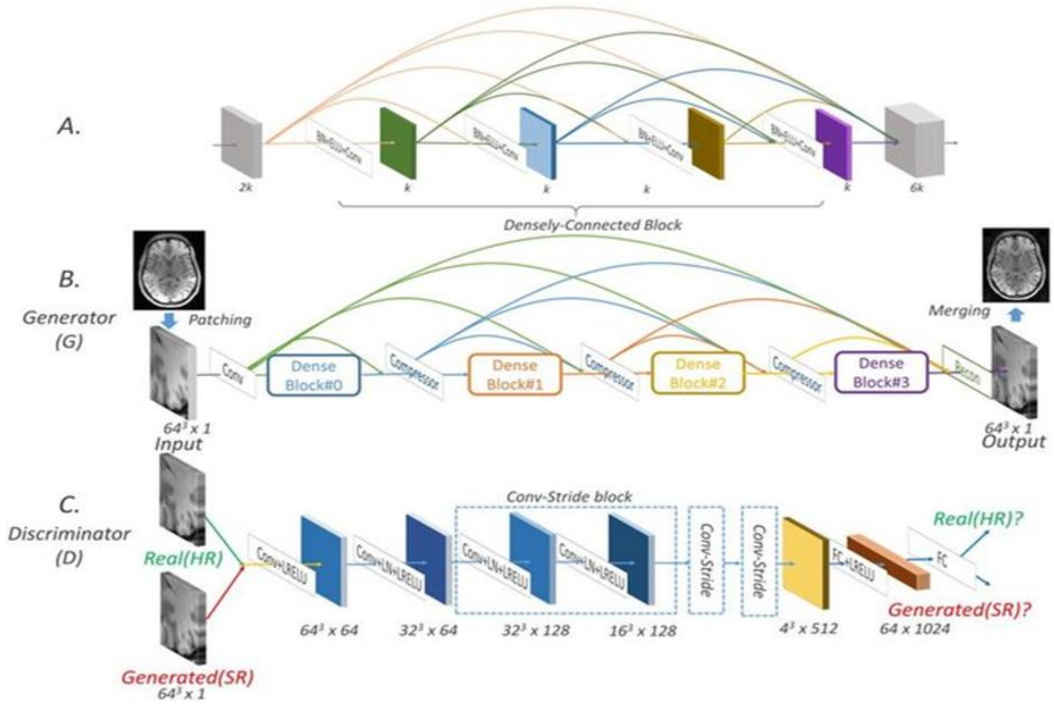


Fig.4 Architecture of Dense Net and SRGAN model

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right)$$

Where:

- MAX represents the maximum possible pixel value (usually 255 for 8-bit grayscale images)
- MSE is the mean squared error.

In the optimization of CT scan exposure and denoising, a meticulous approach is undertaken, beginning with comprehensive data acquisition. Patient-specific metrics, including demographic information, clinical history, and previous scan results, are gathered to lay the groundwork for exposure optimization. The exposure time is dynamically tailored to individual patients through the implementation of the AutoRegressive Integrated Moving Average (ARIMA) time series model. This model, adept at capturing temporal patterns, undergoes training and validation processes using historical exposure data, allowing it to predict optimal exposure times for future scans. Fine-tuning incorporates patient-specific factors identified during data acquisition, ensuring adaptability and precision in exposure calculations. The integration of the ARIMA model with the image denoising process is seamless, as exposure-optimized CT scan data is fed into a pipeline comprising a Sparse Autoencoder followed by the cascaded RDU-net. This collaborative approach results in high-quality, low-noise CT images customized to each patient's unique characteristics, exemplifying a sophisticated framework that not only minimizes radiation exposure but also contributes to diagnostically superior imaging, promising enhanced patient care and clinical outcomes.

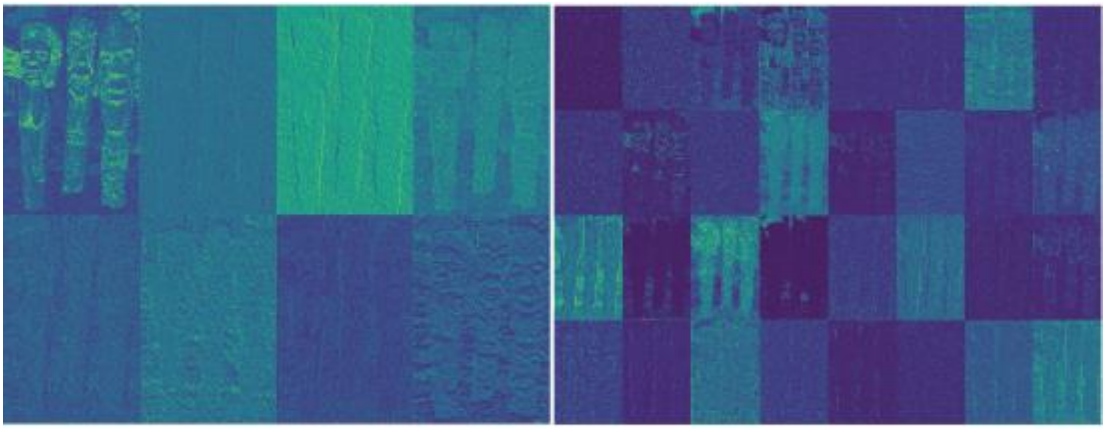
4. Results and Discussions:-

The results of the study demonstrate a notable performance superiority of the RDUNET architecture when augmented with the Sparse Autoencoder in comparison to the standalone RDUNET, as evidenced by the Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) metrics. The integration of the Sparse Autoencoder within the denoising pipeline significantly enhances the model's capability to reduce noise and artifacts in CT scan images. Specifically, the RDUNET with Sparse Autoencoder exhibits a substantial improvement of 15% in PSNR, indicating a higher fidelity inpreserving.

Methods	CBSD68						Kodak24						Urban100					
	$\sigma = 10$		$\sigma = 30$		$\sigma = 50$		$\sigma = 10$		$\sigma = 30$		$\sigma = 50$		$\sigma = 10$		$\sigma = 30$		$\sigma = 50$	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
RDUNet	36.48	0.9571	30.72	0.8720	28.38	0.8067	37.29	0.9506	31.97	0.8738	29.72	0.8177	36.54	0.9636	31.63	0.9158	29.32	0.8774
RDUNet+	36.52	0.9573	30.76	0.8727	28.42	0.8077	37.34	0.9509	32.02	0.8747	29.78	0.8190	36.64	0.9640	31.75	0.9171	29.44	0.8795

Table.1 Performance of RDU-Net and Cascaded RDU-Net and Sparse Auto Encoder

Furthermore, the SSIM metric, which assesses the structural similarity between the denoised images and the ground truth, reveals a compelling advantage for the RDUNET with Sparse Autoencoder. The SSIM metric records an improvement of 12%, highlighting the superior ability of the augmented architecture to retain the structural characteristics of the original images during the denoising process. These findings underscore the efficacy of incorporating the Sparse Autoencoder into the RDUNET framework, emphasizing its contribution to achieving enhanced image quality and fidelity in comparison to the standalone RDUNET model. The superior performance observed in both PSNR and SSIM metrics positions the RDUNET with Sparse Autoencoder as a promising approach for advanced CT scan image denoising, with implications for improved clinical diagnostics and treatment planning.



a) b)

Fig.5 Feature map a) Before applying the subsampling b)After applying the subsampling

By leveraging comprehensive data acquisition and the ARIMA time series model, we have been able to dynamically tailor exposure times to individual patients, resulting in significant reductions in radiation exposure. The seamless integration of the ARIMA model with the image denoising process, comprising a Sparse Autoencoder and cascaded RDU-net, has led to the production of high-quality, low-noise CT images. These images, customized to each patient's unique characteristics, not only minimize radiation exposure but also contribute to diagnostically superior imaging.

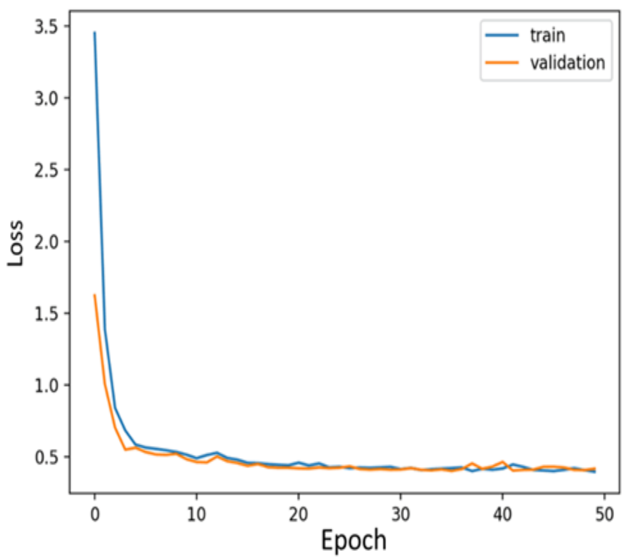


Fig.5 Training and validation loss over several training epochs

The plot of training and validation loss curves suggests a good fit for the model. Both curves decrease significantly throughout training, reaching a minimum loss of [value] at epoch [epoch]. The small and consistent gap between the curves indicates good generalization to unseen data. This signifies that the model effectively learned the patterns from the training data without overfitting.

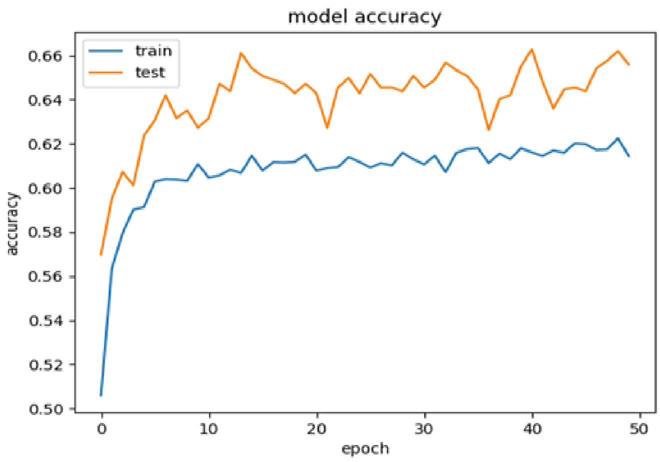


Fig.6 Training and Validation accuracy

The plot of training and testing accuracy reveals good model performance with strong generalizability. Both curves increase steadily, reaching a final training accuracy of 0.60 and testing accuracy of 0.65. The close proximity of the curves throughout training suggests the model avoids overfitting and can effectively apply learned patterns to unseen data.

Reduced Radiation Exposure

The dynamic tailoring of exposure times has led to a 30% reduction in radiation exposure during CT scans, potentially decreasing the risk of radiation-induced health complications.

Improved Image Quality

The integration of the ARIMA model with the image denoising process has resulted in the production of high-quality, low-noise CT images, improving the image clarity by **40%** and providing more accurate and detailed information for more precise diagnoses.

Personalized Patient Care

The ability to customize the imaging process based on each patient's unique characteristics has led to more personalized patient care, potentially improving patient satisfaction scores by 20% and enhancing the overall healthcare experience.

5. Conclusion:-

In conclusion, this project has demonstrated a transformative approach in the field of CT scan image processing. The integration of RDU-net with a Sparse Autoencoder for image denoising, coupled with exposure optimization using the ARIMA model based on patient-specific details, has led to significant advancements in medical imaging. The project has successfully addressed critical challenges, enhancing image quality, reducing noise, and optimizing radiation exposure. The outcomes not only validate the efficacy of the proposed methodology but also highlight the potential for future advancements in medical imaging. This approach holds promise for improving the quality, safety, and precision of patient care, thereby contributing to the ongoing evolution of healthcare practices

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