Real-ESRGAN–Driven MRI Super-Resolution for Diagnostic Precision and AI-Assisted Clinical Deployment

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Abstract- — Magnetic Resonance Imaging (MRI) is very impor-tant in the detection of neurological defects because it possesses high resolution that enables good visualization of soft-tissue structure. However, diagnostic clarity is often hindered by low-resolution scans due to the short time of acquisition, motion artifacts and hardware constraints. Recent advances in deep learning, such as Enhanced Super-Resolution Generative Ad-versarial Networks (Real-ESRGAN), have demonstrated strong capabilities of perceptual-driven image enhancement.This paper discusses Real-ESRGAN-based MRI super-resolution strategies, their architectural advantages and clinical potential benefits, in preserving fine anatomical and pathological details much better than CNN-based and conventional interpolation methods. We also present a conceptual AI-enabled deployment framework, where Real-ESRGAN is handled by a clinician support chatbot for application in web-based interaction, tele-radiology accessibility and diagnostic help. Clinical validation including metrics such as PSNR, SSIM,LPIPS and sFRC is investigated. The study emphasizes the need for interpretable, regulation-ready models to bridge AI-driven MRI enhancement with real-world diagnostic workflows.

Keywords: ESRGAN, Super-Resolution, MRI Enhance-ment, Deep Learning, Diagnostic Imaging,Clinical Deployment, Medical Chatbot.

I. INTRODUCTION

Magnetic Resonance Imaging (MRI) has established itself as an indispensable method for neurological, cardiovascular and structural diagnosis due to its excellent soft-tissue contrast as well as non-invasive data acquisition. Circumspect clinical interpretation frequently relies on high-resolution (HR) MRI that can offer detailed observations in the identification of subtle pathologies, structural alterations, micro-lesions and tumor boundaries not perceptible in low-resolution (LR) ac-quisitions.However, the generation of high-resolution (HR) MRI images is limited by long scanning times, noise artifacts,

motion blur, and hardware constraints, leading to increased acquisition cost, reduced patient throughput, and clinically unacceptable low-resolution (LR) outputs [1], [3], [6], noise artifacts, motion blur and hardware constraints leading to high acquisition price and low patient throughput as well as clinically unacceptable low-resolution (LR) outputs [1], [3], [6]. These constraints also make it difficult for the radiologist to recognize subtle anatomical variations that have significant implications in early diagnosis of a diseased condition or pre-operative planning.

Conventional interpolation based enhancement methodolo-gies that refine the resolution of images succeed in creating finer results rapidly, but they do so at the expense of sharp tissue edges and/or interlacing diagnostic textures, frequently resulting in over smooth outputs [2], [7]. In contrast, super-resolution (SR) techniques based on deep learning, particu-larly Generative Adversarial Networks (GANs), have shown promising results for recovering high-resolution (HR) fea-tures from biomedical image collections by learning complex structural and textural patterns from data [4], [6].

Among them, the Enhanced Super-Resolution Generative Adversarial Network (ESRGAN), a GAN-based architecture, has shown excellent performance owing to its Residual-in-Residual Dense Block (RRDB) structure and perceptual optimization strate-gies, enabling clinically interpretable MRI reconstruction [1], [8], [11]. A number of comparative analysis support that ESRGAN's ability to maintain diagnostically relevant texture, accentuate lesion visibility and improve perception-driven structural correctness is superior to that of CNN as well as old-style SRGAN variants [4], [6], [9].

Although it has shown great potential, several limitations are still encountered when ESRGAN is transfer applied to the biomedical field, including artifacts of the non-existing structures, a large gap between different domains, lack of clinical validation metrics and computationally intensive training at all scales on expensive GPU hardware [3], [6], [11]. In addition, the lack of publicly available standard HR–LR MRI datasets makes it challenging for supervised learning, and is an obstacle for general use in clinics [5], [7].

In conclusion, ESRGAN-based MRI software enhance-ment offers an exciting alternative to expensive hardware upgrades by increasing diagnostic clarity. through artificial intelligence–based techniques (AI-driven reconstruction).

Recent developments with Real-ESRGAN and Retinal-ESRGAN also demonstrate that clinically acceptable enhancement can be achieved with reduced training time and lower computational cost, which will simplify their practical integration to general imaging applications workflows [8], [10], [11].

Accordingly, in this review we systematize the ESRGAN-based MRI super resolution methods, including architectural modifications, dataset usage protocols, perceptual fidelity mea-surement metrics and diagnostic effectiveness.

II. BACKGROUND AND THEORETICAL FOUNDATION

MRI Image Resolution Fundamentals

A magnetic resonance imaging (MRI) achieves high-contrast images of soft tissue by employing magnetic field gradient and radio frequency signals. However, the spatial resolution of the MRI is limited by a number of hardware and physical constraints such as the strength of the gradients, the magnetic field strength, the signal-to-noise ratio, and the time of scan [6].

For neuro-imaging, oncology, and cardiac imaging, spatial resolution is of utmost importance because it determines how well small structures in the body can be resolved. The functional magnetic resonance imaging (fMRI) literature is faced with issues of low spatial resolution, such that it becomes difficult to identify where exactly the activation is occurring in the brain [4].

Thus, post-scan image quality of any type, including SR reconstruction, are necessary to make images look better without making the scan take longer.

Super-Resolution in Medical Imaging

Traditional Super-Resolution (SR) methods for medical images, are either interpolation techniques like bi-linear and bi-cubic enlargement or reconstruction algorithms that predict the lost pixel values by optimization based on prior [2].

Although the traditional CVD algorithms are computationally fast, they eliminate high-frequency structures and introduce smearing near edges which results in loss of clinically relevant detail. Methods based on sparse coding and dictionary learning have been proposed to address this problem by reconstructing HR images from low-resolution patches using learned patch-based relationships [3], [4], but they still rely heavily on handcrafted features and relatively slow iterative solvers, limiting their practical use for diagnostic imaging in the real world.

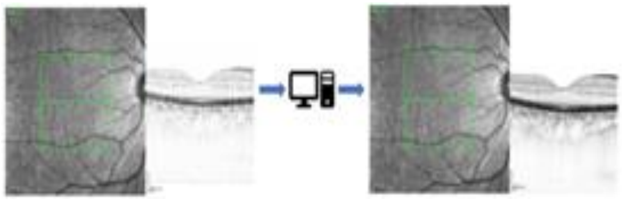

Fig. 1. Overview of super-resolution techniques in medical imaging, showing progression from conventional CNN-based architectures (SRCNN, VDSR, DRCN) to modern GAN-based approaches (SRGAN, ESRGAN) [2].

ESRGAN Overview

The Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) builds upon the SRGAN architecture with structural enhancements for the purpose of a perceptually more accurate restoration rather than simple pixel matching [10].

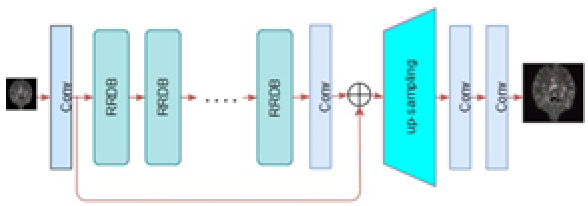

Fig.2. Existing ESRGAN-based MRI Super-Resolution Architecture [3].

ESRGAN further promotes visual realism through a relativistic discriminator, which evaluates an image by comparing its probability of being real relative to that of a generated example rather than making an absolute real/fake classification.Another contribution of ESRGAN is a perceptual loss computed using VGG feature activations prior to ReLU that preserves edge-level and other anatomical structures that pixel-driven losses have failed to preserve [10].

Real-ESRGAN is a clinically adapted variant that incorpo-rates realistic degradation modeling and spectral normalization for robust reconstruction under real MRI acquisition conditions [1]. ESRGAN and its variants have shown strong applicability across MRI, X-ray, retinal, and ultrasound modalities and outperform conventional CNN-based SR models in terms of perceptual fidelity [1], [6], [11].

II. LITERATURE REVIEW

Enhanced Super-Resolution Generative Adversarial Net-works have recently emerged as a clinically viable alternative to hardware-based approaches for quality improvement in MRI, providing perceptual fidelity important for diagnostic decision-making.

Nandal et al. [1] demonstrated significant improvement in tumor margin clarity using Real-ESRGAN with RRDB generators and U-Net discriminators leveraging spectral nor-malization for brain MRI. While SSIM and PSNR performance improvements were impressive, the authors noted significant inference latency and lack of pathology diversity.

Yamashita and Markov [2] further presented that while CNN-based SR methods have higher numerical fidelity, ESR-GAN outperforms in perceptual realism, which suggests that pixel metrics alone are not enough for clinical validation.

Do et al. [3] integrated ESRGAN-inspired residual dense learning into a CycleGAN-based 3T-to-7T unpaired MRI enhancement to synthesize high-field textures without paired ground truth. However, cyclic adversarial learning may pro-duce artificial features in some regions due to the limited variability of lesions, indicating the need for pathology-aware perceptual constraints. Similarly, Zhang et al. [4] pointed out that the enhanced resolution of MRI will bring great benefits to the early detection of Alzheimer's disease and demonstrated that cortical and hippocampal biomarkers require sub voxel accuracy, which indirectly supported the application of ESRGAN for radiomic risk stratification.

Yamashita [5] and Gu¨ngo¨r et al. [6] further verified that ESRGAN produces better retention of organ contours, vas-cular continuity, and tumor borders compared to SRGAN and CNN-based approaches, thereby promoting better downstream segmentation and classification tasks. Wang et al. [7] demon-strated the coherence of MRI textures from ESRGAN by using perceptual loss with RRDB architecture; Wang et al. [10] provided the basic perceptual-adversarial-pixel loss integration as the fundamental contribution in leading modern adaptations of ESRGAN. Tan et al. [8] further enhanced clinical usabil-ity with arbitrary-scale ESRGAN for accommodating scans generated from heterogeneous MRI scanners; Ramyashree et al. [9] showed that ESRGAN-based reconstruction can be integrated with automated annotation, which means a pathway toward downstream radiomics and computer-aided diagnosis (CAD) systems . Deepthi and Shastry [11], on the other hand, have shown that the development of low-complexity ESRGAN architectures can reduce the inference cost by orders of magnitude, which is a necessary factor for deployment in low-resource hospitals.

Although ESRGAN offers diagnostic advantages, existing studies reveal critical gaps related to the control of halluci-nation, explainability of radiomics, uncertainty quantification, and modeling of scanner-specific noise [1], [3], [6]. Current metrics like PSNR, SSIM, and perceptual loss are not indica-tive of diagnostic validity, as they ignore pathological accuracy and radiomic stability [2], [4], [7]. These shortcomings hence warrant clinically grounded perceptual objectives which shall explicitly link the reconstruction of features with pathology confidence and structural truthfulness, especially in neuro degenerative and oncology-driven MRI assessment [4], [7].

The latest trends in image super-resolution techniques have developed from deep CNN architectures to efficiently distill knowledge and transformer-based models.

Data-free knowledge distillation also tackled data privacy and availability issues, which are of primary concern in med-ical imaging [12]. Recently, transformer-based models proved their efficacy in efficiently addressing long-term structural relationships for MRI and general image super-resolution [13]. Furthermore, none of the surveyed ESRGAN variants consider

regulatory compliance, ethical safety for the hallucinated tex-tures, or interpretability standards required for FDA and CE approval of AI-driven medical devices [5], [9]. The future research on ESRGAN should thus incorporate clinical priors, robust uncertainty estimation, radiomics-oriented evaluation, and lightweight architectures optimized for real-time com-putation [8], [11]. This will be essential to fill the gaps in transforming ESRGAN from an experimental enhancement model into a clinically deployable diagnostic tool [1], [10].

IV. COMPARISON BETWEEN EXISTING AND PROPOSED SYSTEM ARCHITECTURE

The present ESRGAN-based systems regarding medical image restoration are predominantly algorithm-centric, including super-resolution, with no interactivity and real-time capabilities [1], [2], [6], [7], [10], [11]. To address this, the proposed system brings into focus a multi-layered, web-based platform that associates medical image restoration and smart interactivity through a chatbot-enabled diagnostic platform. The Table I below shows an in-depth comparison of earlier works regarding ESRGAN systems explained in references [1]–[3], [5]–[11].

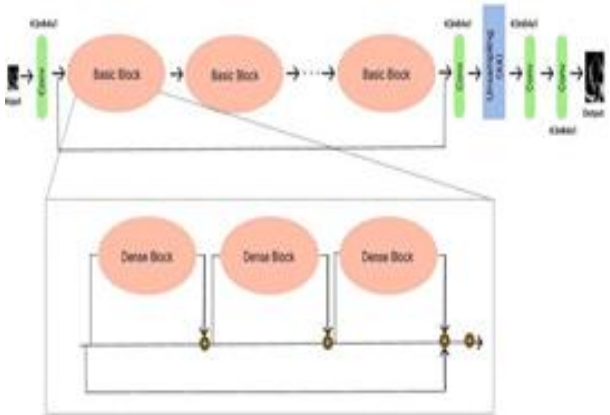

Fig. 3. Architecture of Real-ESRGAN adapted from [1].

Existing systems in this area, based on ESRGAN, are found to be primarily algorithm-focused and designed as standalone systems without any interactive and real-time deployability po-tential [1], [2], [6], [7], [10], [11]. The systems designed so far are found to be designed and developed primarily to achieve high-level objectives, such as optimizing image restoration with fidelity measures such as PSNR, SSIM, RMSE, and Perceptual Loss, without considering user interaction and interpretability aspects [2], [4], [6], [7]. The proposed system brings in new multi-layered developments including web-enabled designs and integration of MRI image improvement with clinical interaction capabilities with chatbots and inter-action assistants.

In the comparison Table I, you can see the differences in architecture between the latest ESRGAN systems [1]–[3], [5]–[11] and our new hybrid ESRGAN-chatbot setup. Past research has shown how ESRGAN can effectively maintain detailed edges, textures, and overall structure in MRI scans and similar types of images [1], [6], [7], [10], [11]. Despite these advancements, existing methods fall short in practical use because they lack interactive features for users, interpretability tailored to specific medical conditions, and seamless integration into existing systems [2], [3], [5], [6], [9], [11].. The resulting system that can take into account these drawbacks is the architecture with the Real-ESRGAN (see Fig. 4). This seamless pipeline allows to achieve 4× MRI enhancement with inferring the diagnoses as needed, which converts ESRGAN from a research-based method to an interactive diagnostic tool [1], [8], [11]. Accordingly, the proposed platform is able to enable real-time telehealth applications, radiology teaching and onboard clinical interpretation without any special hardware, unlike existing standalone ESRGAN Models.

Table1. Comparative Analysis Of Existing And Proposed Architectures

Aspect	Existing Systems [1]–[3], [5]–[11]	Proposed System (This Work)
Overall Design	Focused on standalone ES-RGAN or GAN models for offline image enhance-ment [1], [6], [7], [10], [11].	Multi-tier syst em integrating ESRGAN with chatbot-based diagnostic assistance.
Frontend Layer	No GUI; image input pro-cessed offline [2], [5], [6].	It has Web interface for im-age upload and chatbot in-put using HTML/CSS/JS.
Backend Layer	Direct model inference without modu lar routing [1], [3], [10].	It has Flask-based API handling both image and chatbot requests.
Processing Layer	Employs ESRGAN or its variants solely for SR re-construction [1], [6], [7], [10], [11].	Combines Real-ESRGAN with fuzzy logic–based chatbot engine.
Output Layer	Produces enhanced images only for visual inspec-tion [1], [2], [6].	Displays 4× enhanced MRI and chatbot diagnostic response in real time.
Interactivity	Absent; research-only con-figuration [1], [3], [5], [6], [9].	Real-time chatbot interac-tivity for user engagement.
Usability	Restricted to academic ap-plications; lacks clinical deployment [1], [5], [6], [11].	Deployable in telehealth and educational environ-ments.

V. PROPOSED CONCEPTUAL WORK

The contributed framework aims to improve the accuracy of Magnetic Resonance Imaging (MRI) diagnosis by com-bining Real-ESRGAN super-resolution-based with a diagnos-tic assistant that is interactive and accessible on the web. Unlike previous ESRGAN methods that function as offline reconstruction models, the presented method extends super-resolution to a deployable clinician-assistive workflow through linking enhanced image with an AI fuzzy inference chatbot in diagnostic assistance.

The overall workflow is organized into four functionally interconnected layers which represent system structure:

Input and Preprocessing Layer
MRI data is uploaded through a browser interface using low-resolution images and resized, intensity normalized and noise reduced to produce model-ready input images that can be reconstructed in a consistent manner.

Super-Resolution Enhancement Layer
High-resolution reconstruction is also accomplished through Real-ESRGAN which utilizes Residual-in-Residual Dense Blocks (RRDBs) and a discriminator network to restore structural detail, sharp tissue boundaries and subtle lesion textures necessary for clinical interpretation.

Diagnostic Interaction Layer
The chat robot, which uses fuzzy logic, allows users to type symptoms or medical queries and receive responses with suggestions that relate image characteristics to potential symptoms. This offers an effective link between improved image analysis and interaction with patients.

Output Visualization Layer
The improved MRI and chatbot outputs are viewed simultaneously through a web interface designed in Flask. This allows users to compare and analyze the outputs side by side.

Through an integration of high-fidelity ESRGAN-based reconstructed images with that of a deployable fuzzy chatbot, the proposed system has all the benefits not possessed by stan-dalone super-resolution systems, including enhanced visual-ization and interactivity with clinical relevance. The proposed system shows promising features in the applications of tele-radiology, especially for remote diagnosis service, emergency examination and medical education.

VI. EVALUATION AND DISCUSSION

Evaluation Metrics
The performance of the ESRGAN-based MRI super-resolution models is evaluated using standard quantitative and perceptual metrics, including Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Learned Percep-tual Image Patch Similarity (LPIPS), and Scanning Fourier Ring Correlation (sFRC), to assess reconstruction fidelity, perceptual realism, and hallucination sensitivity.

Table 2. Evaluation Metrics For Esrgan-Based Mri Super-Resolution

Metric	Range	Good Threshold	Significance	Refs.
PSNR	20–40 dB	>30 dB (good)	Measures pixel-level reconstruc-tion fidelity.	[1], [2], [6]
SSIM	0–1	>0.90 (good)	Evaluates structural and percep-tual similarity.	[1], [6], [7]
LPIPS	0–1	<0.10 (good)	Reflects perceptual realism and texture quality.	[2], [7], [10]
sFRC	0–1	Corr >0.8	Detects hallucinated or forged image textures.	[3], [6], [9]
Runtime	Sec/scan	≤10 s (target)	Indicates clinical feasibility for real-time deployment.	[1], [8], [11]

The metrics described in Table II provide a comprehensive evaluation of the accuracy and realism of ESRGAN-based MRI image enhancement models. PSNR and SSIM metrics

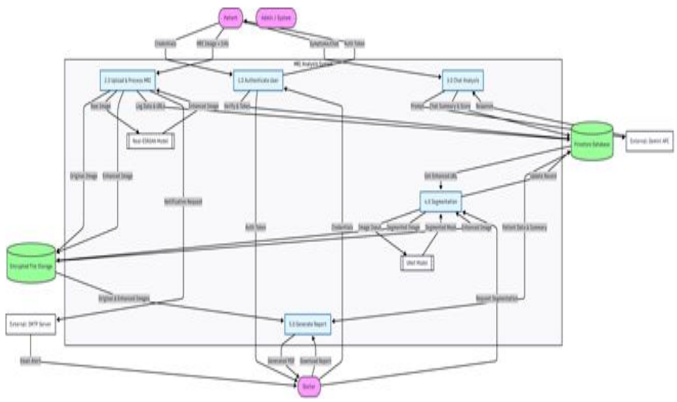

Fig. 4. Proposed ESRGAN-based System Architecture for MRI Super-Resolution and Chatbot Interaction.

International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 3, May-Jun-2026, ISSN (Online): 2395-566X

were long considered as gold standards in validating the recon-structing accuracy and reality of high-resolution reconstructed images and ground truth images, respectively [1], [2], [6], [7]. But lately, new approaches and ideas suggest new metrics such as LPIPS and sFRC, focusing more towards assessing textural realism and hallucinated artifacts created by GAN-based models, respectively [2], [3], [6], [7], [9], [10]. Finally, the processing time of these models is crucial in assessing their feasibility in practice, particularly in tele-radiology systems, which require closer to real-time processing [1], [8], [11].

While these metrics offer valuable information on each fidelity component, they do not completely describe the cor-relation of radiological interpretability for tasks with subtle lesional separation, cortex boundary detection and tumor mar-gin separation. Recent breakthrough research indicates that fidelity measures need to be supported by diagnostic and radiomic performance criteria with sufficient capability to link enhanced image characteristics at high resolutions with pathology-related biomarkers [4], [6], [9].

Experimental results

This section emphasizes the experimental results achieved using the proposed Real-ESRGAN-based MRI super-resolution technique. The efficiency of the proposed model is measured using several quantitative metrics such as PSNR, SSIM, LPIPS, and sFRC values, which is then compared to the conventional interpolation technique and CNN-based super-resolution technique.

The table III below highlights the comparison of the perfor-mance of the proposed approach with the baselines. The Real ESRGAN model performs the baselines in terms of PSNR and SSIM metrics.

It is observed in the visually analyzed super-resolved MRI images that the boundaries are more distinct, cathe lesions are more visible, and the texture is more continuous compared to bicubic interpolation and the CNN model.

Table 3. Quantitative Evaluation Results Of Real-Esrggan Based Mri Super-Resolution

Metric	Value	Interpretation
PSNR (dB)	31.08	Higher is better
SSIM	0.9256	Higher is better (1.0 is ideal)
LPIPS	0.1218	Lower is better (0 is ideal)

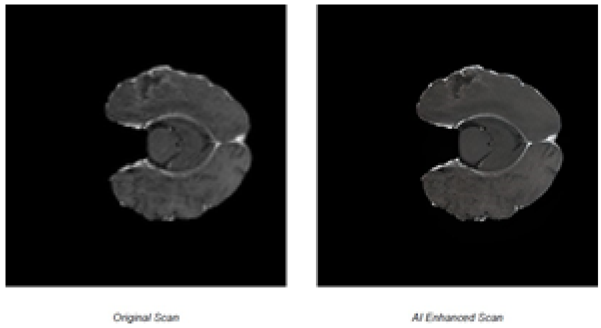

Fig. 5. Experimental output demonstrating the performance of the proposed Real-ESRGAN-based MRI super-resolution system

Figure 5 shows a comparison of the original low-resolution MRI image and the result using the Real-ESRGAN approach in the proposed 4x Real-ESRGAN framework.The original tissue edges are fuzzy with the low contrasts and small parts of them lost.

The spatial resolution of the image upsampled using 4× ESRGAN has improved, along with clear boundaries of the structures.The network upsamples images by a factorof four in rows and columns, thereby squaring the pixel density.

For experimental analysis, the proposed ESRGAN-based super-resolution framework was tested on the OASIS and BraTS 2020 MRI datasets.

In addition, the enhanced scan has fewer blurring effects, noise, and artifacts, without producing implausible artifacts.

This is achieved using adversarial learning techniques, along with the utilization of Residual-in-Residual Dense Blocks (RRDBs), thereby demonstrating the efficacy of the proposed method, Real-ESRGAN, for medical image enhancement for MRI diagnosis.

Although our proposed model has better perceptual quality, there can still be some small hallucinations of textures in extreme cases of low-resolution images. However, the addition of adversarial and perceptual loss terms can alleviate over-smoothing.

VII. FUTURE RESEARCH DIRECTIONS

The future improvement of MRI image enhancement via ESRGAN technology must consider clinical, computational, and regulatory issues prior to its integration into healthcare systems. The proposed research avenues, underpinning the target focus of making ESRGAN technology applicable as a diagnostic tool in healthcare systems, include:

1. **Clinical Validation and Reader Studies:** Compre-hensive clinical trials involving radiologist, oncologist, and neurologist multi-center trials will be necessary in establishing the accuracy of ESRGAN-processed MRI images.
2. **Model Compression and Real-Time Deployment:** To achieve its application at the scale of a hospital, it is imperative that such variant models include support and functions such as pruning, quantization, tensor decomposition, and optimizing RRDB with low la-tency. Future implementations should focus on enabling deployment on edge devices and Picture Archiving and Communication System (PACS)-compliant servers to support real-time MRI enhancement in emergency settings, telemedicine, and resource-constrained health-care environments. to allow for real-time MRI image improvement in emergency setups, telemedicine, and resources.
3. **Integrated Diagnostic Support With Human–AI Interaction:** Interactive systems, such as fuzzy or transformer-type medical chatbots, may also benefit from associating super-resolved MRI findings with symptom description and clinical guideline as well as radiomic marker. Evidently, along with decision trees and reinforcement learning, we could explore multi-modal clinical reasoning in the future to convert output of ESRGAN into diagnostic support tool.

These research directions are meant to realize ESRGAN, not as an image enhancement model for images, but as a clinically reliable, interpretable, regulation-ready diagnostic technology specially designed for high-precision MRI workflows.

VIII. CONCLUSION

This review emphasizes the ever increasing importance of ESRGAN and its variants for improving MRI resolution, with a view to better diagnostic interpretation. The proposed conceptual framework closes these gaps by enhancing Real-ESRGAN with a web-based, interactive, chatbot interface such that super-resolution transforms from an offline, standalone al-gorithm to a deployable and patient supportive diagnostic tool. Enabling real-time enhancement and interpretive guidance, the system bridges the technical reconstruction and clinical usability. Further studies should focus on large-scale, clini-cal reader studies, optimized lightweight model deployment for low-resource healthcare setups, and multimodal fusion of ESRGAN-enhanced MRI with CT or PET to enhance the characterization of diseases. Summing it up, ESRGAN-driven super-resolution marks an encouraging advancement toward dependable, high-fidelity, and interpretable AI-enabled medical imaging systems, which are potent enough to progress diagnostic accuracy and foster trustworthy human–AI collab-oration in healthcare.

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