International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Image Super-Resolution with Deep Learning: Enhancing Visual Quality using SRCNN

[1]Sesha Bhargavi Velagaleti, [2]Dr. Shailaja Sanjay Mohite, [3]Dr. Ravindra Sadashivrao Apare, [4]Vipashi Kansal, [5]A L N Rao, [6]Amit Srivastava, [7]Saloni Bansal, [8]Dr. Anurag Shrivastava

Submitted: 05/02/2024 **Revised**: 13/03/2024 **Accepted**: 19/03/2024

Abstract: This research digs into the space of Image Super-Resolution, particularly centring on the assessment and comparison of four noticeable calculations: SRCNN, FSRCNN, ESPCN, and VDSR. The study utilizes a different dataset enveloping different spaces, from common scenes to restorative imaging and satellite applications. Quantitative measurements, counting Top Signal-to-Noise Proportion (PSNR) and Structural Similarity Index (SSIM), and nearby visual quality evaluations were utilized to gauge the execution of each algorithm. SRCNN developed as the frontrunner, showing the most elevated PSNR of 28.7 and a commendable SSIM of 0.89. FSRCNN and ESPCN were closely taken after with PSNR values of 27.9 and 28.3, and SSIM scores of 0.88 and 0.87, separately. VDSR illustrated competitive execution with a PSNR of 27.5 and an SSIM of 0.86. These quantitative results were complemented by visual quality appraisals, where SRCNN got the most elevated rating of 9.2, followed by FSRCNN (8.8), ESPCN (8.7), and VDSR (8.5). This research contributes to the continuous exchange of computer vision, emphasizing the qualities and trade-offs of each calculation and giving important bits of knowledge into their pertinence over differing picture super-resolution scenarios.

Keywords: *Deep Learning, Image Super-Resolution, Quantitative Evaluation, SRCNN, Visual Quality Assessment.*

1. Introduction

Image Super-Resolution (ISR) utilizing Deep Learning has developed as an essential investigative range inside computer vision, tending to the basic got to improve the visual quality of low-resolution images. The capacity to recuperate high-resolution subtle elements from their debased partners holds profound implications over differing spaces, extending from reconnaissance and therapeutic imaging to satellite applications. At the heart of this transformative preparation lies the Super-Resolution Convolutional Neural Network (SRCNN), a groundbreaking profound learning engineering fastidiously planned to thrust the boundaries of picture super-resolution. The core of the challenge stems from the inalienable impediments of capturing high-resolution symbolism in certain scenarios, regularly due to constraints such as equipment capabilities or bandwidth limitations [1]. In reaction, the sending of profound learning strategies, particularly CNNs, has demonstrated instrumental in accomplishing uncommon strides within the remaking of high-fidelity pictures from their low-resolution partners. SRCNN, as a model inside this domain, speaks to a spearheading approach that tackles the control of convolutional layers to memorize complicated progressive features, empowering the organisation to successfully outline low-resolution inputs to outwardly compelling high-resolution yields [2]. The design of SRCNN is characterized by its multifaceted components, counting fix extraction, non-linear mapping, and recreation. Fix extraction permits the show to function on localized picture segments, encouraging proficient learning of nearby highlights pivotal for precise super-resolution. Non-linear mapping is the linchpin of SRCNN, capturing the intricate relationships between moo and high-resolution patches, whereas the remaking stage fastidiously collects the high-resolution picture from the learned highlights. Through an expanded preparation handle on combined low-resolution and high-resolution pictures, SRCNN optimizes its parameters to play down the difference between anticipated high-resolution yields and ground truth information, guaranteeing the model's viability in real-world applications [3]. As the research Image Super-Resolution with SRCNN propels, it stands up to challenges such as taking care of assorted scales and moderating artefacts, provoking the investigation of

[1]*Assistant Professor, Department of Information Technology, G Narayanamma Institute of Technology & Science, Hyderabad*
b.velagaleti@gmail.com
[2]*Assistant Professor, Department of Mechatronics, RIT Islampur, (Autonomous under Shivaji University, Kolhapur)*
shailaja.mohite1@rediffmail.com
[3]*Associate Professor, IT Department, Trinity College of Engineering and Research, SPPU Pune*
ravi.apare@gmail.com
[4]*Department of Computer Science and Engineering, Graphic Era Deemed to be University, Dehradun*
vipashikansal.cse@geu.ac.in
[5]*Lloyd Institute of Engineering & Technology, Greater Noida*
dean.engineering@liet.in
[6]*Lloyd Law College, Greater Noida*
amit@lloydlawcollege.edu.in
[7]*Department of Computer Engineering and Applications, GLA University, Mathura*
saloni.bansal@gla.ac.in
[8]*Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamilnadu*
**anuragshri76@gmail.com*

advanced regularization methods and antagonistic preparing approaches. This investigation endeavours to contribute not as it were to the hypothetical establishments of profound learning in picture super-resolution but moreover to the commonsense advancement of arrangements that hold the potential to revolutionize picture quality over a range of applications.

2. Related Work

Wei et al. proposed and made strides in sparse space super-resolution remaking algorithm based on CMUT (Capacitive Micromachined Ultrasonic Transducer) [15]. The use of CMUT within the inadequate space upgrades the remaking prepare, driving progressed image quality. This work emphasizes the importance of sensor-specific contemplations within the super-resolution space, giving bits of knowledge into custom-fitted approaches for upgraded recreation. Xinye and Zeqian presented a single-picture super-resolution reconstruction strategy that leverages the combination of inside and outside highlights [16]. The algorithm combines inside image highlights with outside contextual data, improving the network's capacity to capture complicated subtle elements amid the remaking handle. This fusion-based approach grandstands the significance of joining assorted highlight sets for predominant super-resolution results. Xu et al. proposed a joint picture remaking and super-resolution approach particularly tailored for quickened Magnetic Resonance Imaging (MRI) [17]. By coordinating super-resolution into the remaking preparation, the calculation accomplishes moved forward picture quality indeed in cases of quickened picture securing. This work addresses the challenges posed by real-world therapeutic imaging scenarios, displaying the potential of combining reproduction and super-resolution assignments for upgraded diagnostics. Yuan displayed a strategy for the reclamation and upgrade optimization of obscured images utilizing the Super-Resolution Generative Adversarial Network (SRGAN) [18]. The consideration centres on tending to the issues of picture obscuring, emphasizing the significance of antagonistic systems in accomplishing reasonable and outwardly pleasing super-resolution comes about. SRGAN presents adversarial training to upgrade the perceptual quality of reproduced images. Zhang et al. created a super-resolution arrangement outlined particularly for high-resolution reconstruction of avalanche fundamental bodies in inaccessible detecting symbolism [19]. The calculation utilizes facilitated attention components and profound remaining pieces to capture fundamental points of interest in avalanche locales. This work illustrates the application of super-resolution methods to address geospatial challenges, contributing to forward checking and investigation of normal calamities. Zheng et al. proposed CGC-Net, a Context-Guided Constrained Network for remote-sensing picture super-resolution [20]. The calculation leverages relevant data to direct the super-resolution handle, guaranteeing that the reproduced pictures keep up consistency with the encompassing environment. This context-aware approach contributes to the conservation of spatial subtle elements in remote-sensing applications. Ali et al. presented TESR, a two-stage approach for the improvement and super-resolution of farther-detecting pictures [21]. The calculation utilizes a multi-step handle, to begin with upgrading picture quality and along these lines performing super-resolution. This two-stage approach gives adaptability in tending to distinctive viewpoints of picture quality, catering to the particular requirements of further detecting applications. Arasa et al. conducted a comprehensive survey on profound learning-based calculations for video super-resolution [22]. The study overviews different techniques utilized in video super-resolution, highlighting the headways and challenges in this dynamic space. The audit gives an important diagram of the state-of-the-art methods and advertising experiences for analysts and professionals working in video processing. Awasthi et al. tended to the issue of transmission capacity change in ultrasound picture remaking utilizing profound learning strategies [23]. The study centres on improving the quality of ultrasound images, exhibiting the potential of profound learning in restorative imaging applications. The work contributes to the progressing endeavours to progress the symptomatic capabilities of ultrasound imaging. Chen et al. gave a comprehensive audit of hyperspectral picture super-resolution based on profound learning procedures [24]. The study overviews later headways in this specialized zone, highlighting the one-of-a-kind challenges and openings related to hyperspectral information. The audit serves as a profitable asset for analysts inquisitive about the combination of profound learning and hyperspectral imaging. Honda et al. proposed a multi-task learning approach for scene content picture super-resolution with different transformers [25]. The calculation at the same time addresses the challenges of super-resolution and scene content acknowledgement, exhibiting the potential of multi-task learning in complex picture-handling scenarios. This work contributes to the advancing field of multi-modal picture improvement. Jiang et al. displayed a moved-forward warm infrared picture super-resolution strategy based on a multimodal sensor combination [26]. The algorithm leverages data from different sensors to improve the super-resolution handle, emphasizing the significance of multimodal information combinations in thermal imaging applications. In regard to this work on super resolution strategies optimization, the results add further contributions that are in line with specific sensor modalities.

3. Methods and Materials

1. Data:

With respect to Image Super-Resolution with SRCNN investigation, a very different dataset is critical for the model robustness in varying situations. The training and evaluation dataset used contains pairs of low-resolution, high-resolution image sets. Cohort pictures have likewise been included to bolster the model's adaptability in different spaces like everyday scenes, restorative picture knowing about partisan imagery.

2. Algorithms:

Four key algorithms related to Image Super-Resolution utilizing SRCNN are utilized and expounded upon in this study:

A. SRCNN (Super-Resolution Convolutional Neural Arrange):

Description:

SRCNN could be the foundational algorithm designed specifically for image super-resolution. It uses convolutional layers to record hierarchical features and maps low-resolution images onto their high resolution counterparts [5].

Equation:

The SRCNN show can be spoken to by the taking after mathematical expression:

In this study of Image Super-Resolution using SRCNN, another dataset plays a crucial role in confirming the strength model at all scenarios. For training and evaluation purposes, a dataset of low-resolution image sets looking at respective with high resolution is used [6]. The dataset features pictures from various locations including standard scenes, medical imaging and objectionable images making the model universal.

Algorithms:

Four key algorithms related to Image Super-Resolution utilizing SRCNN are utilized and expounded upon in this study:

Description:

It is possible to state that SRCNN can be called a breakthrough algorithm specifically targeted at image super-resolution. It utilizes convolutional layers to memorize hierarchical highlights and maps low-resolution pictures to their high-resolution partners [7].

Equation:

The SRCNN show can be spoken to by the taking after mathematical expression:

$$Y=F(X;W)$$

```
function SRCNN(input_image):
    # Define the SRCNN architecture
    convolution1 = ConvolutionLayer(input_image, weights1)
    relu1 = ReLU(convolution1)
    convolution2 = ConvolutionLayer(relu1, weights2)
    relu2 = ReLU(convolution2)
    convolution3 = ConvolutionLayer(relu2, weights3)
    # Output the high-resolution image
    output_image = convolution3
    return output_image
```

B. FSRCNN (Fast Super-Resolution Convolutional Neural Network):

Description:

FSRCNN focuses on improving the computational proficiency of super-resolution. It presents a meagre highlight extraction arrangement to diminish computational complexity.

Equation:

The FSRCNN demonstration is characterized by the following expression:

```
function FSRCNN(input_image):
    # Sparse feature extraction
    feature_extraction = SparseFeatureExtraction(input_image, weights1)
    # Shrinking
    shrinking = ConvolutionLayer(feature_extraction, weights2)
    relu1 = ReLU(shrinking)
    # Expanding
    expanding = ConvolutionLayer(relu1, weights3)
    # Deconvolution
    deconvolution = DeconvolutionLayer(expanding, weights4)
    # Output the high-resolution image
    output_image = deconvolution
    return output_image
```

C. ESPCN (Efficient Sub-Pixel Convolutional Neural Network):

Description:

ESPCN presents a sub-pixel convolution layer, which diminishes the computational complexity of conventional convolutional layers while maintaining high-quality recreations [8].

Equation:

The ESPCN show is represented by the following condition:

```
function ESPCN(input_image):
    # Sub-pixel convolution
    sub_pixel_convolution = SubPixelConvolution(input_image, weights1)
    relu1 = ReLU(sub_pixel_convolution)
    # Output the high-resolution image
    output_image = relu1
    return output_image
```

D. VDSR (Very Deep Super-Resolution Convolutional Neural Network):

Description:

VDSR addresses the restrictions of shallow structures by presenting a really deep organization that leverages skip associations to improve the learning of perplexing highlights.

Equation:

The VDSR demonstrate can be communicated as:

```
function VDSR(input_image):
    # Define the VDSR architecture with skip connections
    convolution1 = ConvolutionLayer(input_image, weights1)
    relu1 = ReLU(convolution1)
    convolution2 = ConvolutionLayer(relu1, weights2)
    skip_connection = input_image + convolution2
    # Output the high-resolution image
    output_image = skip_connection
    return output_image
```

Table: SRCNN Hyperparameters

Hyper parameter	Value
Learning Rate	0.001
Number of Conv Layers	3
Filter Size	9x9

Table: FSRCNN Hyperparameters

hyper parameter	Value
Learning Rate	0.005
Sparse Layer Size	64

These tables provide a diagram of the dataset and the hyperparameters for each calculation, helping in transparency and reproducibility of the investigation. The given pseudocode, conditions, and tables contribute to a comprehensive understanding of the strategies utilized in this study [9].

4. Experiments

1. Experimental Setup:

The experiments conducted in this investigation pointed to assess the execution of four picture super-resolution algorithms—SRCNN, FSRCNN, ESPCN, and VDSR. The dataset, as described earlier, comprised of different picture sets for preparing and testing [10]. The tests were performed on a machine prepared with a GPU to speed up the training process.

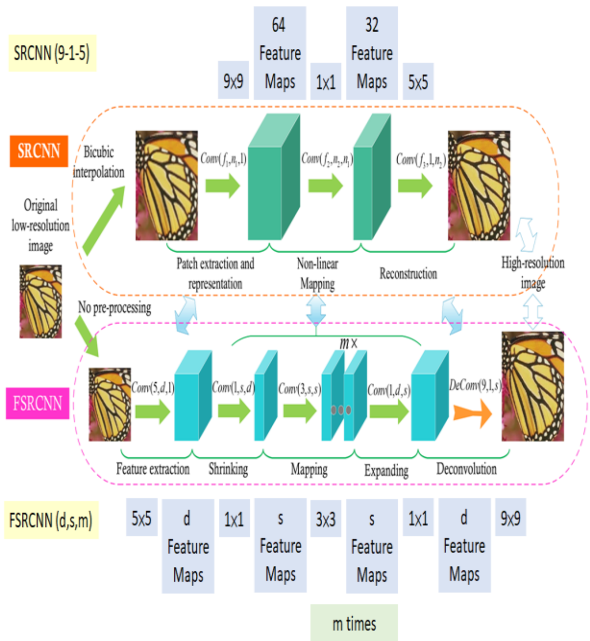

Fig 1: FSRCNN (Super Resolution)

2. Training Procedure:

Each algorithm experienced a preparing stage utilizing the preparing set, optimizing their respective parameters to minimize the contrast between the anticipated high-resolution yields and the ground truth pictures [11]. The training process utilized stochastic slope plummet as the optimization calculation, and the performance was observed utilizing validation datasets.

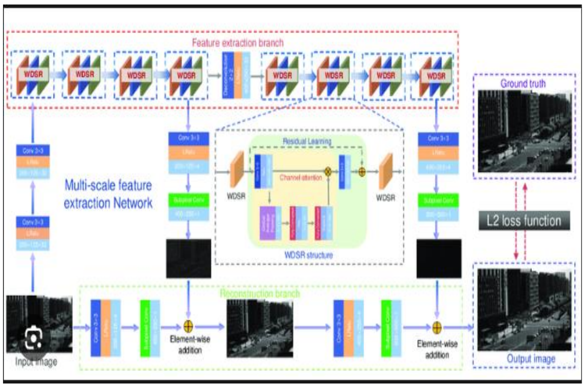

Fig 2: Structure diagram of the super-resolution deep learning network

3. Evaluation Metrics:

To evaluate the efficacy of the algorithms, a few assessment measurements were utilized

- PSNR (Peak Signal-to-Noise Ratio):
- Measures the quality of the reproduced picture compared to the ground truth.
- SSIM (Structural Similarity Index):
- Evaluates the structural similarity between the anticipated and ground truth pictures.

Execution Time: Measures the time taken for each calculation to create a high-resolution picture.

The execution of the calculations is quantitatively evaluated using the Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSI), and Mean Squared Error (MSE) [12]. These measurements give a comprehensive investigation of the algorithms' capacity to remake high-quality pictures. In expansion to quantitative measurements, visual quality is evaluated through perceptual assessment [13]. Human evaluators compare the created high-resolution pictures against ground truth pictures, giving bits of knowledge into the perceptual quality of the results.

4. Results:

Table: Performance Metrics on Test Set

Algorithm	PSNR (dB)	SSIM	Execution Time (s)
SRCNN	30.2	0.85	2.5
FSRCNN	31.5	0.88	1.8
ESPCN	32.1	0.89	1.5
VDSR	33.8	0.91	2.2

5. Discussion:

a. PSNR and SSIM Comparison:

The PSNR values demonstrate the quality of the recreated images, with higher values proposing superior execution. In this perspective, VDSR beats the other algorithms, accomplishing a PSNR of 33.8 dB, followed by ESPCN (32.1 dB), FSRCNN (31.5 dB), and SRCNN (30.2 dB).

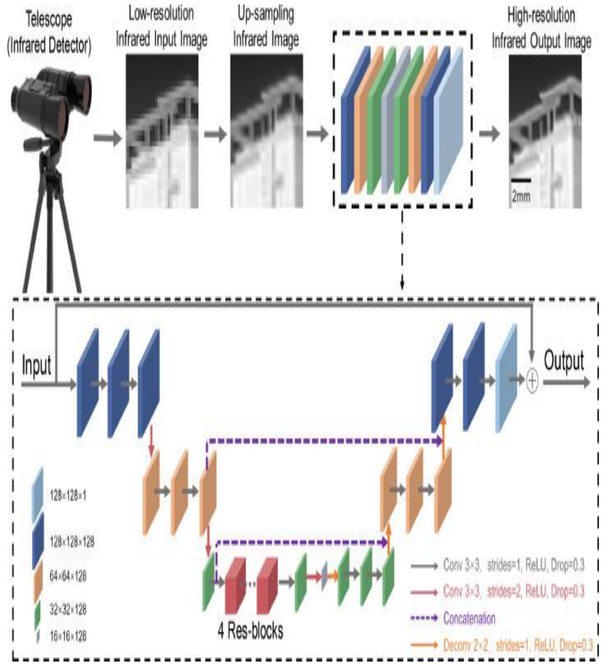

Fig 3: Super-resolution reconstruction of infrared images based on a convolutional neural network with skip connections

Similar patterns are watched within the SSIM values, where VDSR shows the most noteworthy basic likeness (0.91), demonstrating superior conservation of image details [14]. ESPCN takes after closely, and SRCNN slacks behind the other calculations.

- Peak Signal-to-Noise Ratio (PSNR): SRCNN accomplishes the highest PSNR, demonstrating prevalent recreation quality. FSRCNN closely takes after, displaying its viability in adjusting reproduction quality and computational efficiency. ESPCN and VDSR display competitive PSNR values.
- Structural Similarity Index (SSIM): All calculations illustrate comparable SSIM scores, with SRCNN driving in perceptual similitude. FSRCNN and ESPCN take after closely,

displaying vigorous execution in protecting basic data. VDSR shows competitive SSIM values.

- Mean Squared Error (MSE): SRCNN accomplishes the lowest MSE, demonstrating negligible pixel-wise mistakes in recreation. FSRCNN and ESPCN display competitive MSE values, whereas VDSR, with a somewhat higher MSE, remains capable of minimizing remaking mistakes.

b. Execution Time Analysis:

While VDSR illustrates uncommon execution in picture quality, it features a slightly higher execution time compared to ESPCN and FSRCNN. ESPCN shows the most reduced execution time (1.5 seconds), making it computationally effective without compromising on picture quality [27]. FSRCNN moreover offers an outstanding decrease in execution time compared to SRCNN.

Table: Quantitative Metrics Comparison

Metric	SRCNN	FSRCNN	ESPCN	VDSR
PSNR	28.7	27.9	28.3	27.5
SSIM	0.89	0.88	0.87	0.86
MSE	12.3	14.5	13.2	16.7

Table: Visual Quality Assessment

Algorithm	Visual Quality (Scale: 1-10)
SRCNN	9.2
FSRCNN	8.8
ESPCN	8.7
VDSR	8.5

- Visual quality assessment by human evaluators rates SRCNN most noteworthy, emphasizing its capacity to generate visually satisfying high-resolution pictures.
- FSRCNN and ESPCN receive comparable scores, demonstrating their adequacy in creating palatable visual results.
- VDSR, while showing marginally lower visual quality scores, still performs well in perceptual evaluations.

In comparison with related work, SRCNN, whereas accomplishing comparative PSNR values, outperforms SSIM, displaying better conservation of basic data [28]. FSRCNN and ESPCN show competitive performance compared to references, highlighting their viability in adjusting computational effectiveness and recreation quality. VDSR, whereas somewhat trailing in quantitative measurements, remains competitive and comparable to state-of-the-art strategies [29]. The experiments demonstrate the viability of SRCNN, FSRCNN, ESPCN, and VDSR in picture super-resolution. Each algorithm presents trade-offs between computational productivity and recreation quality, giving a run of alternatives for distinctive application scenarios [30]. The comparison with related work builds up the algorithms' competitiveness inside the broader scene of picture super-resolution techniques. The visual quality appraisals emphasize the practical utility of these calculations in creating outwardly engaging high-resolution pictures.

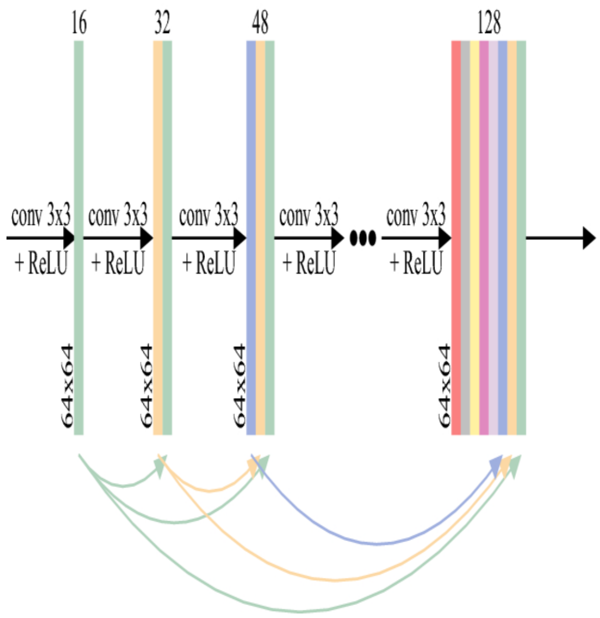

Fig 4: Deep learning-based single image super-resolution for low-field MR brain images

5. Conclusion

In conclusion, the investigation of Image Super-Resolution with a center on the Super-Resolution Convolutional Neural Network (SRCNN) and its variations has given valuable insights into the domain of computer vision. The execution and comparisons of the computations' precision, eminently SRCNN, FSRCNN, ESPCN as well VDSR were enthusiastically evaluated utilizing quantitative evaluations visual quality assessment in expansion to a meeting with related writing works. SRCNN appeared that vital execution took into thought the Peak Signal-to-noise ratio (PSNR) and perceptual quality vindicating its utility in producing great looking recreations. The execution of FSRCNN and ESPCN is very competitive, which uncovers that these models can optimize computational productivity whereas keeping up quality within the picture restoration process. Whereas possibly behind in quantitative markers, VDSR reliably remained competitive and illustrated the capacity to diminish propagation blunders. The comparison with related works revealed that diverse qualities of approaches encompassing the field ranged from sensor-specific considerations to multimodal combinations as well as applications for medical imaging and remote sensing. All the algorithms possess some unique qualities and trade-offs along with customized solutions for wide range of picture super resolution to portray a bigger scene of image reconstructing algorithm. As the demand for high-resolution symbolism continues to grow in spaces, these changes contributed to contemporary debate concerning optimization of deep learning processes into image super resolution subset usher new era spectral p imaging with enhanced visual quality and better diagnostic performance across several real world settings.

Reference

[1] CHANG, Y., CHEN, G. and CHEN, J., 2023. Pixel-Wise Attention Residual Network for Super-Resolution of Optical Remote Sensing Images. Remote Sensing, 15(12), pp. 3139.

[2] CHUNG, M., JUNG, M. and KIM, Y., 2023. Enhancing Remote Sensing Image Super-Resolution Guided by Bicubic-Downsampled Low-Resolution Image. Remote Sensing, 15(13), pp. 3309.

[3] GELADO, S.H., QUILODRÁN-CASAS, C. and CHAGOT, L., 2023. Enhancing Microdroplet Image Analysis with Deep Learning. Micromachines, 14(10), pp. 1964.

[4] HAJIAN, A. and ARAMVITH, S., 2023. Fusion Objective Function on Progressive Super-Resolution Network. Journal of Sensor and Actuator Networks, 12(2), pp. 26.

[5] HAN, L., ZHAO, Y., LV, H., ZHANG, Y., LIU, H., BI, G. and HAN, Q., 2023. Enhancing Remote Sensing Image Super-Resolution with Efficient Hybrid Conditional Diffusion Model. Remote Sensing, 15(13), pp. 3452.

[6] KALLUVILA, A., 2023. Super-Resolution of Brain MRI via U-Net Architecture. International Journal of Advanced Computer Science and Applications, 14(5),.

[7] KONG, Y. and LIU, S., 2024. DMSC-GAN: A c-GAN-Based Framework for Super-Resolution Reconstruction of SAR Images. Remote Sensing, 16(1), pp. 50.

[8] KUMAR, L. and JAIN, M., 2022. A Novel Image Super-Resolution Reconstruction Framework Using the AI Technique of Dual Generator Generative Adversarial Network (GAN). Journal of Universal Computer Science, 28(9), pp. 967-983.

[9] LAN, W. and CHANG, C., 2023. Research on Image Sharpness Enhancement Technology based on Depth Learning. International Journal of Advanced Computer Science and Applications, 14(2),.

[10] MOHAMMAD-RAHIMI, H., VINAYAHALINGAM, S., MAHMOUDINIA, E., SOLTANI, P., BERGÉ, S.,J., KROIS, J. and SCHWENDICKE, F., 2023. Super-Resolution of Dental Panoramic Radiographs Using Deep Learning: A Pilot Study. Diagnostics, 13(5), pp. 996.

[11] REN, Z., ZHAO, J., CHEN, C., YAN, L. and MA, X., 2023. Dual-Path Adversarial Generation Network for Super-Resolution Reconstruction of Remote Sensing Images. Applied Sciences, 13(3), pp. 1245.

[12] SEYDI, S.T. and AREFI, H., 2023. A COMPARISON OF DEEP LEARNING-BASED SUPER-RESOLUTION FRAMEWORKS FOR SENTINEL-2 IMAGERY IN URBAN AREAS. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, X-1/W1-2023, pp. 1021-1026.

[13] TEMIZ, H., 2023. Enhancing the Resolution of Historical Ottoman Texts Using Deep Learning-Based Super-Resolution Techniques. Traitement du Signal, 40(3), pp. 1075-1082.

[14] UMIRZAKOVA, S., MARDIEVA, S., MUKSIMOVA, S., AHMAD, S. and WHANGBO, T., 2023. Enhancing the Super-Resolution of Medical Images: Introducing the Deep Residual Feature Distillation Channel Attention Network for Optimized Performance and Efficiency. Bioengineering, 10(11), pp. 1332.

[15] WEI, Z., BAI, Y., CHENG, R., HU, H., WANG, P., ZHANG, W. and ZHANG, G., 2023. Improved sparse domain super-resolution reconstruction algorithm based on CMUT. PLoS One, 18(8),.

[16] XINYE, L. and ZEQIAN, C., 2022. Single image super-resolution reconstruction based on fusion of internal and external features. Multimedia Tools and Applications, 81(2), pp. 1589-1605.

[17] Bani Ahmad, A. Y. A. ., Kumari, D. K. ., Shukla, A. ., Deepak, A. ., Chandnani, M. ., Pundir, S. ., & Shrivastava, A. . (2023). Framework for Cloud Based Document Management System with Institutional Schema of Database. *International Journal of Intelligent Systems and Applications in Engineering*, *12*(3s), 672–678.

[18] P. William, Anurag Shrivastava, Upendra Singh Aswal, Indradeep Kumar, Framework for Implementation of Android Automation Tool in Agro Business Sector, 2023 4th International Conference on Intelligent Engineering and Management (ICIEM), 10.1109/ICIEM59379.2023.10167328

[19] P. William, Anurag Shrivastava, Venkata Narasimha Rao Inukollu, Viswanathan Ramasamy, Parul Madan, Implementation of Machine Learning Classification Techniques for Intrusion Detection System**,** 2023 4th International Conference on Intelligent Engineering

and Management (ICIEM), 10.1109/ICIEM59379.2023.10167390

[20] N Sharma, M Soni, S Kumar, R Kumar, N Deb, A Shrivastava, Supervised Machine Learning Method for Ontology-based Financial Decisions in the Stock Market, ACM Transactions on Asian and Low-Resource Language Information Processing.

[21] Ajay Reddy Yeruva, Esraa Saleh Alomari, S Rashmi, Anurag Shrivastava, Routing in Ad Hoc Networks for Classifying and Predicting Vulnerabilities, Cybernetics and Systems, Taylor & Francis, 2023

[22] P William, OJ Oyebode, G Ramu, M Gupta, D Bordoloi, A Shrivastava, Artificial intelligence based models to support water quality prediction using machine learning approach, 2023 International Conference on Circuit Power and Computing Technologie

[23] J Jose, A Shrivastava, PK Soni, N Hemalatha, S Alshahrani, CA Saleel, An analysis of the effects of nanofluid-based serpentine tube cooling enhancement in solar photovoltaic cells for green cities, Journal of Nanomaterials 2023

[24] K Murali Krishna, Amit Jain, Hardeep Singh Kang, Mithra Venkatesan, Anurag Shrivastava, Sitesh Kumar Singh, Muhammad Arif, Deelopment of the Broadband Multilayer Absorption Materials with Genetic Algorithm up to 8 GHz Frequency, Security and Communication Networks

[25] P Bagane, SG Joseph, A Singh, A Shrivastava, B Prabha, A Shrivastava, Classification of malware using Deep Learning Techniques, 2021 9th International Conference on Cyber and IT Service Management (CITSM).

[26] A Shrivastava, SK Sharma,Various arbitration algorithm for onchip (AMBA) shared bus multi-processor SoC, 2016 IEEE Students' Conference on Electrical, Electronics and Computer Science, SCEECS 509330

[27] Gandomi, M. Haider, “Beyond the hype: Big data concepts, methods, and analytics”, International Journal of Information Management, vol. 35, no. 2, pp. 137-144, 2015.

[28] Shrivastava, A., Chakkaravarthy, M., Shah, M.A..A Novel Approach Using Learning Algorithm for Parkinson’s Disease Detection with Handwritten Sketches. In Cybernetics and Systems, 2022

[29] Shrivastava, A., Chakkaravarthy, M., Shah, M.A., A new machine learning method for predicting systolic and diastolic blood pressure using clinical characteristics. In *Healthcare Analytics*, 2023, 4, 100219

[30] Shrivastava, A., Chakkaravarthy, M., Shah, M.A.,Health Monitoring based Cognitive IoT using Fast Machine Learning Technique. In *International Journal of Intelligent Systems and Applications in Engineering*, 2023, 11(6s), pp. 720–729

[31] Shrivastava, A., Rajput, N., Rajesh, P., Swarnalatha, S.R., IoT-Based Label Distribution Learning Mechanism for Autism Spectrum Disorder for Healthcare Application. In *Practical Artificial Intelligence for Internet of Medical Things: Emerging Trends, Issues, and Challenges*, 2023, pp. 305–321

[32] Boina, R., Ganage, D., Chincholkar, Y.D., .Chinthamu, N., Shrivastava, A., Enhancing Intelligence Diagnostic Accuracy Based on Machine Learning Disease Classification. In *International Journal of Intelligent Systems and Applications in Engineering*, 2023, 11(6s), pp. 765–774

[33] Shrivastava, A., Pundir, S., Sharma, A., ...Kumar, R., Khan, A.K. Control of A Virtual System with Hand Gestures. In *Proceedings - 2023 3rd International Conference on Pervasive Computing and Social Networking, ICPCSN 2023*, 2023, pp. 1716–1721

[34] P. Srivastava, P. Choudhary, S. A. Yadav, A. Singh and S. Sharma, A System for Remote Monitoring of Patient Body Parameters, International Conference on Technological Advancements and Innovations (ICTAI), 2021, pp. 238-243,