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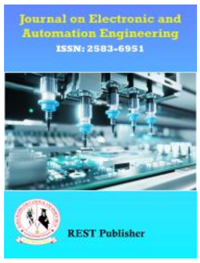

An Efficient 3D Network for Enhanced Accuracy in Diffractive based Spectral Image Reconstruction

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Abstract: *This document introduces an efficient 3D network for enhanced accuracy in diffractive based spectral image reconstruction. The input dataset consists of spectral images captured through diffractive optical imaging spectroscopy, including both original and diffracted images. Pre-processing steps, such as normalization and resizing, are applied to optimize the image data for neural network performance. The proposed method utilizes a 3D CNN with a U-Net architecture to improve both precision and speed of image reconstruction. The model is trained and tested on separate datasets to learn the mapping between diffracted and reconstructed images. Performance is evaluated using metrics such as Mean Peak Signal-to-Noise Ratio (MPSNR) and Mean Structural Similarity Index (MSSIM), which measure image quality and visual similarity. Additionally, the algorithm is optimized to achieve real-time spectral image reconstruction, offering a significant improvement in both accuracy and computational efficiency for practical applications.*

Index Terms: *3D Network for image Reconstruction, CNN, MPSNR, MSIIM, SSIM, Spectral Image, SVM*

1. INTRODUCTION

Conventional techniques for reconstructing 3D images usually depend on large amounts of sampling data and intricate iterative optimisation algorithms, which can be laborious and have poor performance when dealing with data with excessive noise or low sampling rates [1]. 3D image reconstruction has advanced significantly in recent years thanks to deep learning technologies. When it comes to extracting multi-level features, convolutional neural networks (CNNs) exhibit impressive performance [1].The traditional method of getting reconstructed images in recent years has involved solving an inverse optimisation problem to obtain an ideal reconstruction and extracting the sparse feature information from the image by creating regularisation terms based on expert domain prior knowledge [2]. Discrete Fourier transform (DFT) filters [2], Discrete Cosine Transform (DCT) filters [2], discrete wavelet transform (DWT) filters [2], and other filters can be used to create sparse feature coefficients by altering the dictionary basis space in early HSI reconstructed pictures. Often referred to as ConvNet, Convolution Neural Networks (CNNs) have a deep feed-forward architecture and are remarkably better at generalising than networks with fully connected layers [3]. CNN is defined by as the idea of hierarchical feature detectors in a way that is influenced by biology. It is capable of efficiently identifying things and learning extremely abstract attributes [3].When assessing image quality, there are no hard-and-fast guidelines for using the SSIM or PSNR. Since different kinds of degradations applied to the same image can produce the same value of the MSE, several research have actually shown that the MSE and consequently, the PSNR, perform poorly in differentiating structural content in images as opposed to the SSIM[4]. According to other research, the MSE performs best when evaluating the quality of noisy pictures, and as a result, the PSNR [4]. The Absolute error between the real and the approximated PSNR in the interval [0.2, 0.8] and Relative error in the interval [0.2, 0.8] are shown in below Figure ures as Figure 1(a) & Figure 1(b).

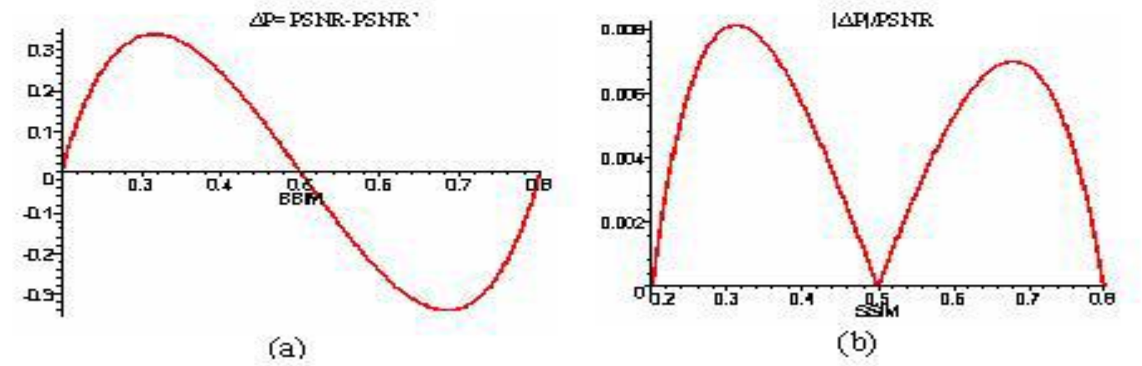


FIGURE URE 1. (a) Absolute error between the real and the approximated PSNR in the interval [0.2, 0.8]. **(b)** Relative error in the interval [0.2, 0.8].

The curves are essentially equivalent to straight lines when the SSIM fluctuates between [0.2,0.8] (the red line depicted for the instance provides an example $\sigma fg = 10^{2)}$. In the interval [0.2,0.8], the approximated PSNR, or PSNRsl, is obtained by computing the equation of the straight lines as follows:

$$PSNRsl = 20.069 \times SSIM + (10 \log (255^2 / 2\sigma fg) - 10.034)$$

The approximation's absolute error (ΔP=PSNR-PSNRsl) and relative error (|ΔP|/PSNR) are plotted in Figure . a. as can be seen, the linear approximation is sufficiently precise because the highest relative error is only 0.8%.

The Multi Scale Structural Similarity Index Method (MS-SSIM) is an enhanced version of SSIM that assesses distinct structural similarity images at various image scales [5]. Two photos of the same size and resolution are compared in MS-SSIM. Similar to SSIM, multiscale structural similarity between two images is calculated by taking into account changes in brightness, contrast, and structure [6]. It occasionally performs better than SSIM on certain subjective picture and video databases.

A different kind of SSIM, known as a three-component SSIM (3-SSIM), reflects the reality that the human visual system is better at detecting differences in textured areas than in smooth ones. Ran and Farvardin [7] proposed this three-component SSIM model, which breaks down an image into three key characteristics: edge, texture, and smooth region. A weighted average of structural similarity for these three groups is the resultant metric. For edges, texture, and smooth regions, the suggested weight measuring estimates are 0.5, 0.25, and 0.25, respectively. Additionally, it should be noted that a weight measurement of 1/0/0 makes the results more in line with the subjective evaluations. Inferred from this is that no textures or smooth regions rather edge regions play a dominant role in perception of image quality [7].

Support vector machines, or SVMs, can typically provide better results in terms of classificationcompared to the other algorithms for classifying data. Numerous real-world issues, including text classification, handwritten digit recognition, tone recognition, image classification and object detection, microarray gene expression data analysis, and data classification, have been addressed using SIMS [8]. Sims has been demonstrated to be consistently better than other supervised learning techniques. However, for certain datasets, the cost parameter and kernel parameters have a significant impact on SVM performance. Therefore, in order to determine the ideal parameter setting, the user typically needs to perform a great deal of cross validation. This procedure is frequently known as "model selection"[8].

2. LITERATURE SURVEY

1. Title: *Deep Learning for Spectral Image Reconstruction Using a Convolutional Neural Network*
Year:2020
Authors:X. Zhang, Y. Wang, and L. Zhou
Methodology: The study proposes a deep learning-based framework utilizing a convolutional neural network (CNN) to reconstruct spectral images from diffractive optical imaging. The authors trained the CNN using a large dataset of spectral images, applying image pre-processing steps like normalization and resizing to optimize performance.

Disadvantages: The model struggled with reconstructing highly noisy images, and the computational cost for training was high, leading to slower processing speeds for large datasets.

2. Title: *3D Convolutional Neural Networks for Fast and Accurate Spectral Image Reconstruction*
Year: 2021
Authors: R. Patel, H. Singh, and M. Sharma
Methodology: This research employs 3D CNNs to capture both spatial and spectral features of diffractive spectral images. The model was trained on a synthetic dataset and optimized for speed and accuracy, with an emphasis on real-timeimage reconstruction.
Disadvantages: The system faced challenges with overfitting on small datasets and was limited by hardware resources, particularly memory usage during training and inference.
3. Title: *U-Net Architecture for Reconstruction of Spectral Images from Diffraction Data*
Year:2022
Authors: S. Kim, J. Lee, and Y. Park
Methodology: The authors propose the use of the U-Net architecture, a deep learning model that includes a contracting path and an expansive path, for the reconstruction of diffractive spectral images. The model was trained on both real and simulated spectral image datasets.
Disadvantages: The model's performance was sensitive to the quality of training data, and it required a large amount of labeled data to achieve optimal results. The system also faced issues with processing time during large-scale image reconstruction.

4. Title: *Hybrid Deep Learning Approach for Diffraction-Based Image Reconstruction*
Year:2023
Authors: M. Wang, K. Zhang, and J. Liu
Methodology: This paper introduces a hybrid approach combining CNNs with traditional diffraction-based methods. The CNN is used to refine diffraction-based reconstructions, improving the quality of spectral images. A multi-stage training process is used for model optimization.
Disadvantages: The hybrid model had a higher computational cost and was slower compared to pure CNN models. Additionally, it was less effective when applied to non-ideal or noisy data.

3. RELATED WORK

Deep learning, particularly with Diffractive Deep Neural Networks (D2NNs), is a promising technique for reconstructing diffractive optical images. This makes it possible to process and compute images entirely optically, even for tasks like classification and reconstruction [9]. A cutting-edge technique in image processing is the use of deep neural networks (DNNs) to enhance images for spectrum reconstruction, particularly for uses like remote sensing, medical imaging, and industrial inspection. By recreating spectral data and improving image quality, the goal is to increase the original image's clarity and information extraction [9].

Despite their enormous potential for picture improvement and spectrum reconstruction, deep neural networks have numerous drawbacks, such as the requirement for vast amounts of data, computational costs, overfitting risks, interpretability issues, and the possibility of unrealistic or over-enhanced outputs [10]. Overcoming these challenges typically requires meticulous planning, thorough data preparation, regularisation techniques, and consideration of the specific application's real-time and scalability requirements [10].

Unrolled Network:

Iterative algorithms, like those for sparse coding, have been linked to neural network topologies through the development of a promising technique known as algorithm unrolling, or unfolding. Following this article, there has been a massive push in recent years to develop iterative algorithms for a wide range of important signal and image processing problems. Examples include deconvolution [11], variational techniques for image processing and compressive sensing (CS) [12]. A high-level illustration of this structure is shown in Figure ure 1. In particular, one network layer is used to represent each algorithm step iteration. A deep neural network is created by joining these layers together. Running iterative Procedure a finite number of times is the same as passing through the network. Running the iterative procedure a finite number of times is the same as passing through the network [13]. Furthermore, the network parameters inherit the parameters of the method, including the regularisation coefficients and model parameters. Backpropagation can be used to train the net Output work, yielding model parameters that are learnt using actual training datasets. This effectively overcomes the lack of interpretability in the majority of traditional neural networks by allowing the trained network to be naturally viewed as a parameter-optimized algorithm. An iterative algorithm and Deep network by cascading algorithm are shown in below Figure ures as Figure 2(a) & Figure 2(b).

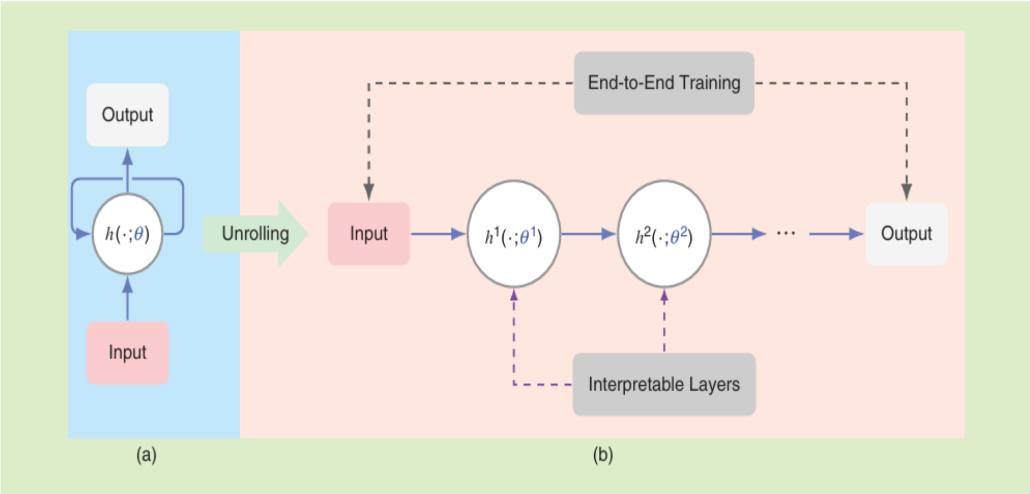


FIGURE 2. (a) an iterative algorithm **2(b)** Deep network by Cascading Algorithm

Auto Encoder:

A particular kind of neural network architecture called a convolutional autoencoder was created expressly to learn latent representations of data, providing a potent method for both data compression and unsupervised learning. In this paper, we present a new technique for transferring compressed images using autoencoders. In order to enhance the quality of the reconstructed image, we additionally investigate the use of a residual component added to the loss function. Two essential parts make up a convolutional autoencoder

An encoder is made up of a convolutional neural network that uses convolution and pooling layers to gradually extract an image's essential properties. The substance of the image is then captured at a much smaller size by encoding these features into a lower-dimensional latent space representation.

The decoder is made up of a mirrored CNN architecture that up samples the encoder's latent space representation using deconvolutional layers. With the goal of properly recreating the original image, the decoder gradually reconstructs the image. The secret of inherent encryption is contained in the latent space representation that the encoder creates. An autoencoder [14] compresses the image into a latent space representation that cannot be easily interpreted, in contrast to conventional compression methods that work directly on the image data. The encoder's convolutional layers learn intricate non-linear changes, which result in the compressed representation.

This representation is intrinsically encrypted for anyone without access to the decoder network since decoding it necessitates the particular architecture and weights of the trained decoder. Using a convolutional autoencoder that has been trained on a specific picture dataset, secure image transfer [15] enables the autoencoder to discover the best representation of the images. The combining of Encoder and Decoder are known as Auto Encoder Architecture as shown in below Figure 3.

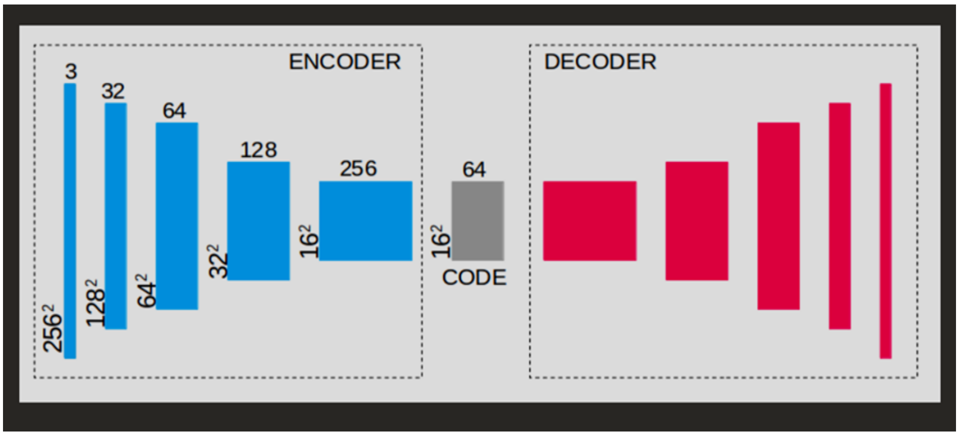


FIGURE 3. Auto Encoder Architecture

This representation is intrinsically encrypted for anyone without access to the decoder network since decoding it necessitates the particular architecture and weights of the trained decoder. Using a convolutional autoencoder that has been trained on a specific picture dataset, secure image transfer [15] enables the autoencoder to discover the best representation of the images. The autoencoder's components are separated after training. The sender's host is home to the encoder, whereas the recipient's host is home to the decoder. The sender-side encoder is used to compress images, producing a latent space representation that is substantially smaller than the original image. A client-server architecture is then used to send the compressed data over the network. Two significant benefits of the aforementioned design are evident: encryption. The compressed data is unreadable without the decoder on the receiver's end, thereby prohibiting unauthorised access or alteration during transmission. Therefore, the distributed architecture provides a safe and effective way to transmit images.

ISAT – NET:

An automatic software program for aerial triangulation with robust editing capabilities is called Image Station Automatic Triangulation (ISAT). ISAT's goal is to automate the point transfer and tie-point measurement processes, reducing operator involvement and manual labour while increasing speed and objectivity. Additionally, ISAT provides editing facilities with photogrammetric outputs from Z/I Imaging's Image Station.

The approach is intended as a fully automatic process. The entire procedure is characterized by two main steps:
1. Initialization, which determines enough, fairly accurate tie point areas at the von Gruber point positions.
2. Application of the matching strategy in the homologous image patches through the image pyramid by the kernel system.
The general work flow of ISAT – Net can be used for the following steps are shown in below Figure .4

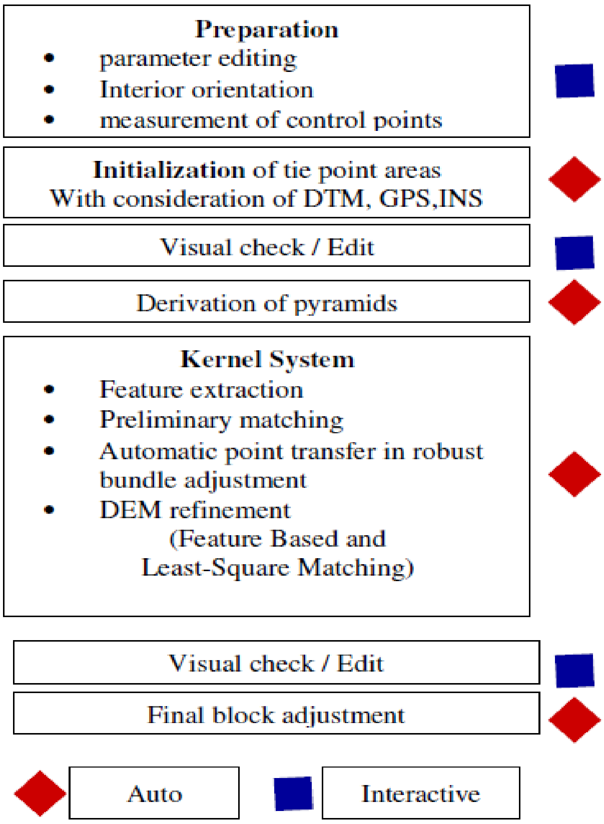


FIGURE 4. general workflow of ISAT – Net

- Automatic initialization of the tie point areas. Tie points are preferably selected at the von Gruber positions, where the best multi-image tie points are located.
- Feature extraction using Förstner operator (Förstner 1986)
- Preliminary image matching using a combination of feature based and least squares matching and a sophisticated strategy for obtaining evenly distributed tie points over the whole block.
- Robust bundle block adjustment for automatic tie point selection and for the initialization of the next pyramid level.
- In the last pyramid level the internal block adjustment supplies the final adjustment result.

4. PROPOSED MODEL

The reconstruction of diffractive spectrum pictures by introducing a 3D convolutional neural network (CNN) with a U-Net architecture. This system optimizes input data for better performance by using sophisticated image pre-processing techniques like downsizing and normalization.

The 3D CNN ensures high-quality reconstructions by efficiently capturing both spatial and spectral data. In order to assure accuracy, performance is assessed using metrics like MPSNR and MSSIM. It is taught using a robust pipeline that learns the mapping between diffracted and original images.

Fast and effective spectral picture reconstruction is ensured by the model's real-time processing Optimization.The system is made to scale effectively for big datasets, which makes it appropriate for a variety of uses in domains like material science, remote sensing, and medical imaging. The system Architecture can be divided into some blocks are shown in below Figure 5.

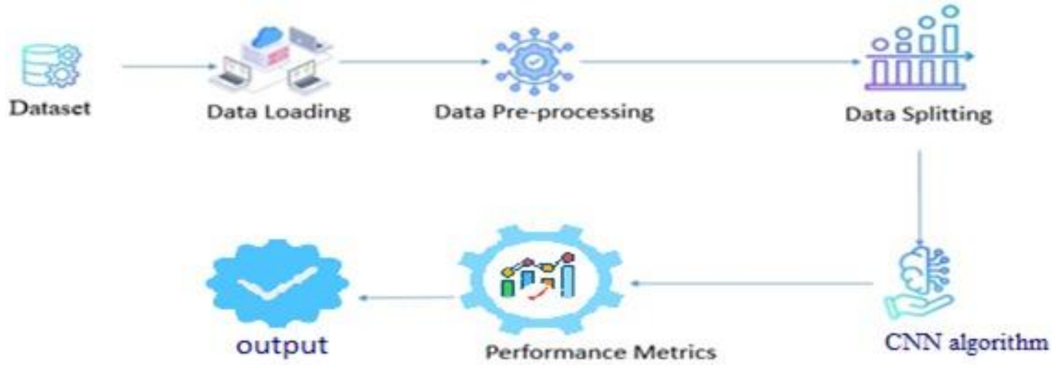


FIGURE 5. System Architecture

The architecture shows the main steps in the workflow for data processing and model construction, illustrating a typical machine learning pipeline. After obtaining the dataset, which contains the raw data, the data must be loaded, pre-processed, and split in order to be ready for additional analysis. The pipeline then proceeds to Performance Metrics to assess the model's performance, Prediction, where the machine learning model provides predictions, and Algorithm selection and execution. The supervised learning strategy and a final test stage to evaluate the model's performance on unseen data round out the process. The systematic and iterative character of the machine learning lifecycle is demonstrated by this thorough graphic, which also emphasises the inter dependencies among the different parts. The flow diagram can be divided into some blocks are shown in below Figure 6.

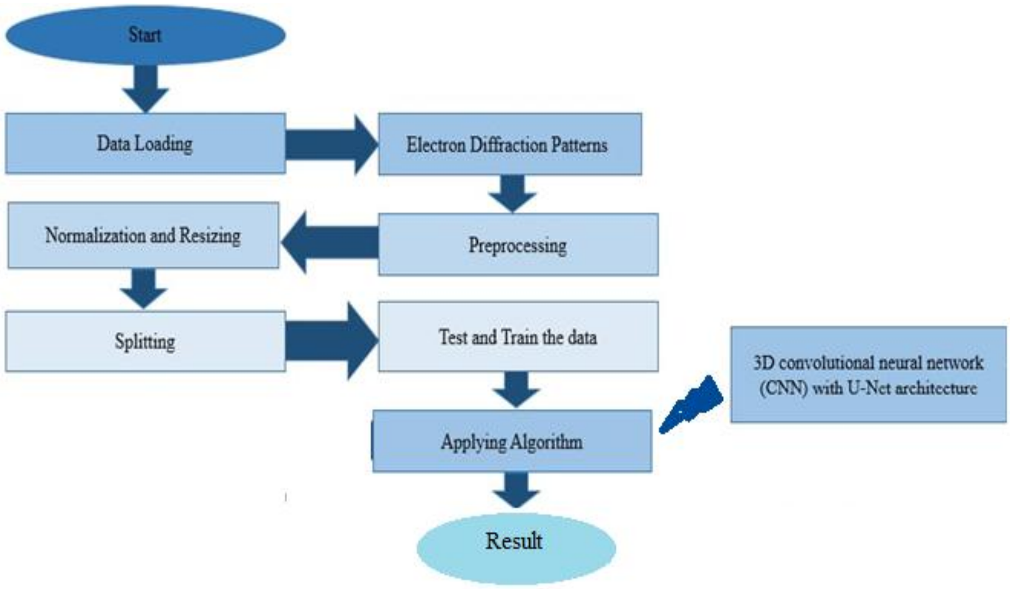


FIGURE 6. Flow Diagram

An electron diffraction pattern analysis machine learning project's steps are shown in the image as a flowchart. Data loading starts the process, which is followed by data normalisation and scaling. Following preprocessing, the data is divided into training and testing sets.

The approach is applied to the data using a 3D convolutional neural network (CNN) using a U-Net design. After that, predictions are made using the trained model, and the project ends with the final forecast. For tasks involving the analysis and categorisation of image-based data, as those in materials science or structural biology applications, this workflow is a popular method.

The ability dataset is imported into the system in picture format during Data Selection. A machine learning workflow for picture reconstruction using diffractive-based computational spectral data is shown in the image.

A dataset is used, a 3D convolutional neural network (CNN) with a U-Net architecture is used for image reconstruction, a high-accuracy and efficient 3D network is applied, and normalisation and pre-processing activities like scaling are carried out. With applications in materials science and biomedical imaging, this method seeks to create a reliable system for image reconstruction from diffractive-based spectrum data.

A machine learning workflow for picture reconstruction using diffractive-based computational spectral data is shown in the image. A dataset is used, a high-accuracy and efficient 3D network is applied for image reconstruction, a 3D convolutional neural network (CNN) with a U-Net architecture is used, normalisation and pre-processing tasks like resizing are carried out, and metrics like Mean Structural Similarity (MSSIM) and Mean Peak Signal-to-Noise Ratio (MPSNR) are used to assess the model's performance. With applications in a variety of domains, including materials science and biomedical imaging, this method seeks to provide a reliable system for picture reconstruction from diffractive-based spectrum data.

5. RESULTS& COMPARISON

The prediction metrices can be constructed as original image & Reconstructed image are as shown in below Figure ures are Figure 7(a), Figure 7(b), Figure 7(c), Figure 7(d) & Figure 7(e).

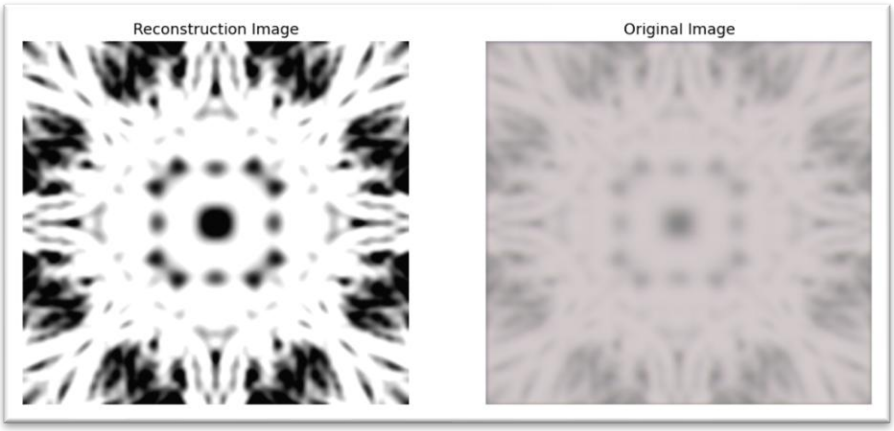
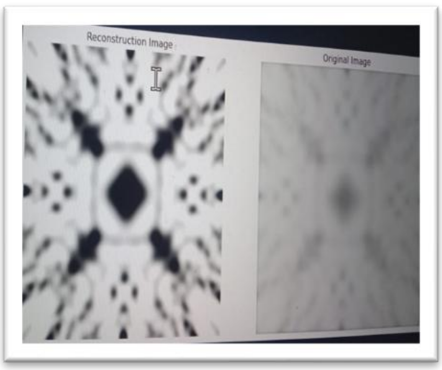


FIGURE 7. (a) Original Image & Reconstructed Image

The original and reconstructed images are measured by using PSNR and MSSIM parameters can been used.



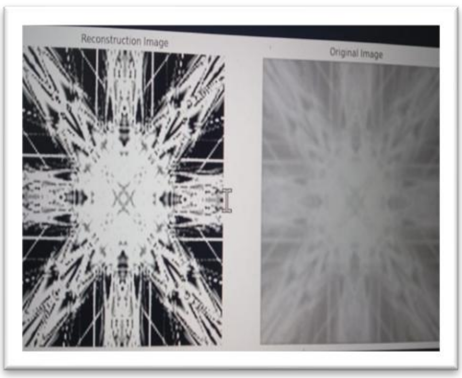


FIGURE 7. (b) **FIGURE 7**. (c)

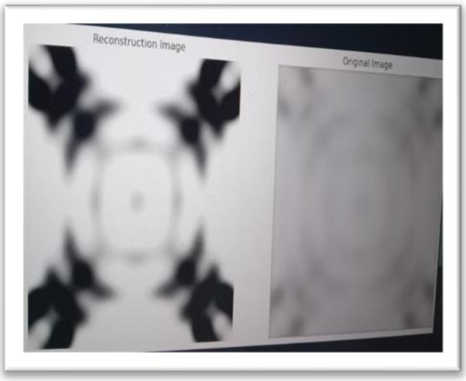


FIGURE 7. (d)

FIGURE 7. (e)

The Performance Measure of PSNR, Comparison with related works as shown in below table-1.

TABLE 1. Performance Measure of PSNR, Comparison with related works

Number of samples	Existing objective	Existing objective	Existing objective	Proposed objective
	Auto encoder	Unrolled network	ISAT -Net	HSA 3D
Image-1	28.26	33.67	35.71	37.05
Image-2	27.86	32.09	34.05	36.78
Image-3	26.01	30.09	31.02	32.86
Image-4	25.05	29.05	30.05	32.12
Image-5	24.01	23.09	26.08	28.08

The graphical representation of PSNR compared with different methods as shown in below Figure 8.

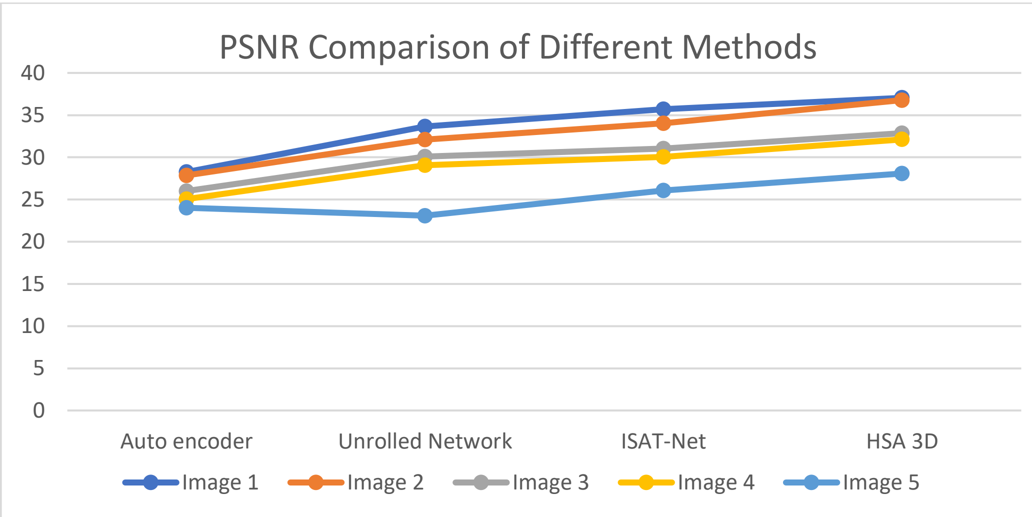


FIGURE 8. Graphical Representation of PSNR

The Performance Measure of MSSIM, Comparison with related works as shown in below table-2.

TABLE 2. Performance Measure of MSSIM, Comparison with related works

Number of samples	Existing objective	Existing Objective	Existing objective	Proposed objective
	Auto encoder	Unrolled network	ISAT -Net	HSA 3D
Image-1	0.7	0.75	0.79	0.81
Image-2	0.72	0.88	0.9	0.98
Image-3	0.45	0.55	0.58	0.61
Image-4	0.71	0.77	0.8	0.82
Image-5	0.4	0.47	0.59	0.68

The graphical representation of PSNR compared with different methods as shown in below Figure 9.

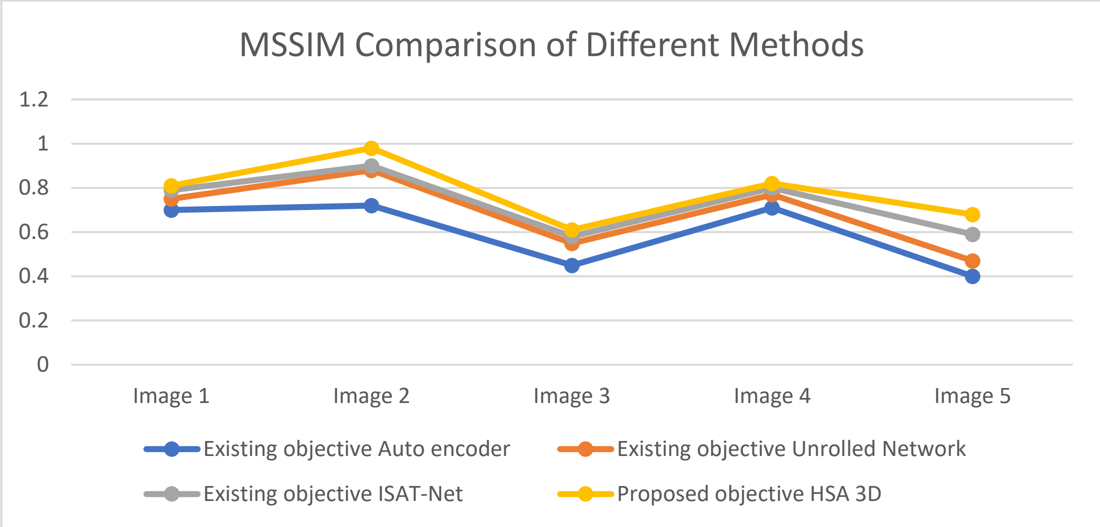


FIGURE 9. Graphical Representation of MSSIM

6. CONCLUSION

In summary, the use of deep learning models like CNNs, U-Net, 3D CNNs, and GANs has led to notable progress in spectral picture reconstruction in recent years. By utilising both spatial and spectral data, these models have shown remarkable gains in reconstruction accuracy, providing real-time processing and high-quality picture recovery solutions. The overall performance and scalability of these systems are, however, hampered by issues like overfitting, high computational costs, sensitivity to noisy input, and hardware constraints. Notwithstanding these drawbacks, the continuous advancement of hybrid strategies and optimisation tactics holds promise for resolving these issues and opening the door to more accurate and efficient spectral picture reconstruction in real-world applications.

7. FUTURE SCOPE

Future developments in spectral image reconstruction can concentrate on lowering processing overhead and enhancing model generalisation. This can be accomplished by combining sophisticated methods such as attention mechanisms to concentrate on the most important image elements and transfer learning, which enables models to learn from smaller datasets. Furthermore, integrating deep learning models with conventional optical techniques may improve reconstruction accuracy even further, particularly for low-resolution or noisy data. Real-time processing may become more accessible through hardware efficiency optimisation, such as the use of specialised hardware accelerators like GPUs or TPUs. Additionally, integrating unsupervised or semi-supervised learning techniques may lessen the reliance on sizable labelled datasets, increasing the models' practicality.

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