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SUPER RESOLUTION BASED DEEP LEARNING TECHNIQUES FOR PANCHROMATIC SATELLITE IMAGES IN APPLICATION TO PANSHARPENING

Prof. Bere Sachin Sukhadeo[1]*, Prof. Salunke Shrikant Dadasaheb[1], Prof. Kadam Swati Amol[1], Prof. Deokate Vasuda Balaso[1], Prof. Dhage Shrikant Narhari[1], Prof. Madane Tai Abaso[1]

[1]*Dattakala Shikshan Sanstha "Dattakala Group of Institution" Swami-Chincholi, Daund, Pune, Maharashtra 413130. India.

***Corresponding Author:** Prof. Bere Sachin Sukhadeo
*Dattakala Shikshan Sanstha "Dattakala Group of Institution" Swami-Chincholi, Daund, Pune, Maharashtra 413130. India.

Abstract:
Pan-sharpening combines multidimensional and panchromatic satellite images to generate higher-resolution products. This research compares standard component replacement and index injection approaches to current deep learning methods such as convolutional and adversarial generative networks. A comparative examination utilizing spatial/spectral quality criteria and visual evaluation demonstrates that deep learning algorithms enhance color and feature retention, despite the greater computing cost. Traditional methods successfully brighten features, but they exhibit greater spectrum aberrations. Overall, this trade-off analysis, informed by quantitative and qualitative performance parameters, aids in the appropriate selection of pan-sharpening paradigms adapted to application goals for high fidelity fused Earth observation data. Deep learning has enormous potential for enhancing the state-of-the-art if spectral integrity is prioritized above spatial sharpness alone.

Index Terms: Pan-sharpening, Deep Learning, Convolutional Neural Networks, Satellite Imagery

I. INTRODUCTION

Image fusion methods may integrate diverse forms of images to provide improved outcomes. A commonly used technique is pansharpening, whereby lower resolution multispectral pictures are fused with more detailed and higher panchromatic images. One disadvantage is that it might cause spectrum distortions due to the characteristics of the panchromatic band. Another method is super-resolution, which employs algorithms to enhance the geographic detail and resolution of a picture. By using super-resolution on the panchromatic imagery prior to merging it with the multidimensional data, the resultant pansharpened picture may exhibit improved resolution and resolution while reducing any distortions in the spectral in- formation. Lately, deep learning super-resolution approaches have shown significant potential. Through the examination of several publically accessible datasets, it was shown that using a feedback network technique yielded better results in accurately recreating intricate features and edges when compared to other approaches. The suggested method first enhances the resolution of the panchromatic imagery and then combines it with the data from multiple spectral bands using a well-established fusion algorithm. Empirical investigations including several sensor datasets demonstrated that this high-resolution enhanced pansharpening technique has the capability to boost spatial detail and edge sharpness while simultaneously mitigating spectral distortions in comparison to traditional methods. In general, including deep learning based high-resolution images into the pansharpening process has the potential to provide images with improved spatial and spectral quality. This is particularly useful for applications that need high resolution photography.

II. AIMS AND OBJECTIVES

A. Aim

The primary aim of the research paper is to examine deep learning oriented super-resolution algorithms to increase panchromatic satellite images spatial precision and resolution. It will merge these super-resolved panchromatic pictures with equivalent multispectral data utilizing pansharpening to pro- vide imagery with better clarity and minimal spectral errors for situations needing excellent quality spatial and spectral information.

B. Objectives

- To analyze and evaluate innovative deep learning-based super resolution approaches for improving panchromatic satellite images.
- To measure the quality of super-resolved panchromatic images using criteria such as sharpness, detail, edge the rebuilding process, and patterns clarity.
- To incorporate high-performing super-resolution technologies into the pansharpening procedure for fusion with

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relevant a multispectral data.

- To evaluate fused images from high-resolution improved pansharpening to increase spatial and spectral quality.
- To showcase the effectiveness of high-resolution preliminary processing on real-world case studies that need high-quality panchromatic data for purposes ranging from urban development to responding to disasters.

III.LITERATURE REVIEW

According to [1], Latest convolutional neural network (CNN) approaches for pansharpening satellite data have showed promise, although they still have deficiencies in output picture quality. We provide a novel self-supervised approach that views pansharpening as an image coloration job. Unlike other CNN systems that super-resolve both a multispectral and panchromatic inputs, our PanColorization adversarial network (PanColorGAN) learns to colorize a grayscale converted mul- tispectral picture during training. In addition, we increase training generalisation to full resolution settings by randomly altering picture downsampling ratios as a data supplementation method. Together with an adversarial training technique, these significant developments assist PanColorGAN in overcoming the spatial detail loss and blurring issues of prior CNN and classic pansharpening systems. Experiments show that the suggested approach is better at recovering fine features along with high fidelity spectral information from satellite picture pairs. Overall, redefining pansharpening as a self-supervised colorization job provides a new viewpoint for advancing CNN- based fusion.

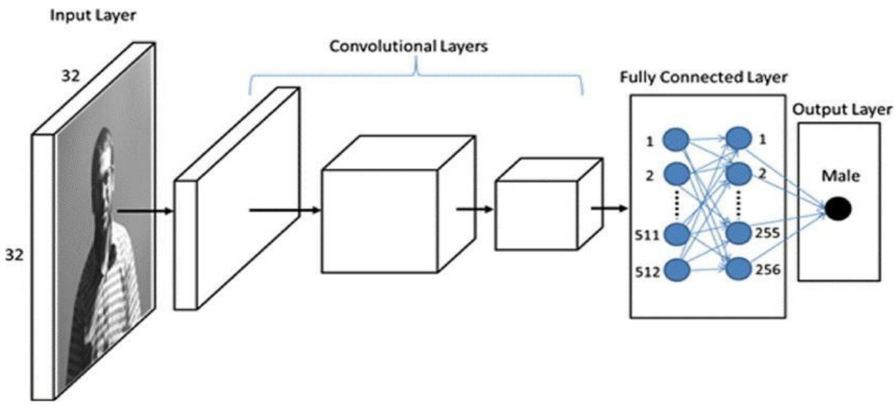

Fig. 1. CNN Model

(Source: https://www.researchgate.net/profile/Bahman- Zohuri/publication/330565196/figure/fig1) According to [2], Pan-sharpening methods are often used to combine multispectral and panchromatic imagery from satellites to improve spatial and spectral resolution. Choosing an effective algorithm that maintains input picture information is difficult [2]. This study includes 41 techniques divided into four categories: component substitution (CS), multi-resolution analysis (MRA), variational optimization (VO), and several mixed methods. Performance was measured using 21 picture pairings from sensors such as WorldView, GeoEye, QuickBird, and Pleiades. Neural network approaches were rejected because to their high processing needs. The algorithms were tested using spectral and geographical quality indicators. The Analysis of Variance evaluated categories statistically. The results reveal that MRA techniques kept spectral attributes better than hybrid approaches, which yielded greater spatial quality. CS had a poor score. The revised Additive Wavelet Luminance Proportional approach topped the spectrum rankings, while the Generalized Intensity-Hue-Saturation fusion version was the sharpest spatially. Run times show that CS is the quickest, although several MRA and VO approaches are slower. In conclusion, no particular pansharpening model predominated across all criteria. However, analysis helps to match procedures to application requirements, balancing the speed of processing with optimal spectral or spatial resolution.

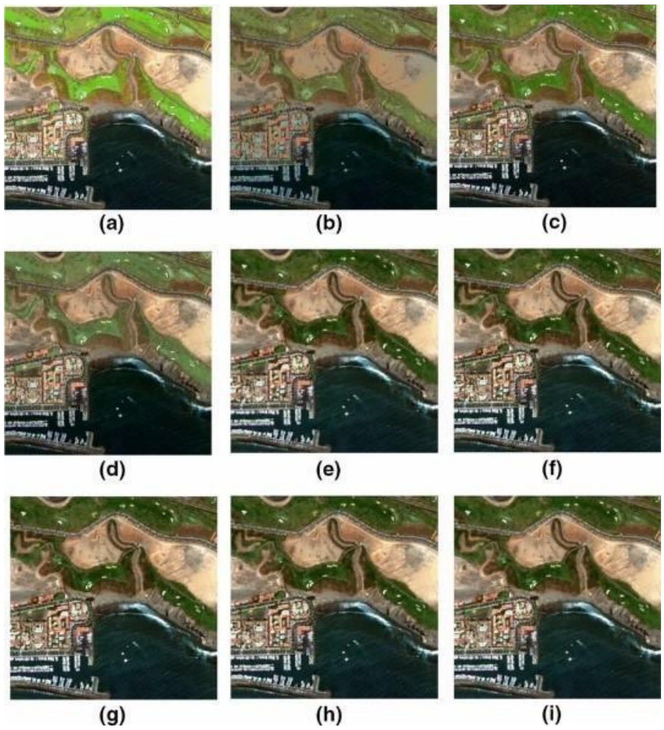

Fig. 2. Pan-sharpening working

According to [3], Pan-sharpening is an important remote sensing operation that combines panchromatic and multi-dimensional satellite pictures to provide synthetic imaging with higher spatial and spectral resolutions. Deep learning techniques have recently evolved in addition to classical algorithms. This study compares and evaluates different cutting- edge approaches. Three deep learning models are compared:
CNN-based (PNN),multiscale convolutional neural network (CNN) (MSDCNN), and generative adversarial network (PS- GAN). Traditional methods include Brovey, PCA, intensity- hue-saturation (IHS), Indusion, and PRACS. Stability is investigated throughout different forms of land cover. Additional studies look at the effects of filter size, spectral indices, activations, and loss functions. Quality measures with and without references enhance visual judgment to quantify correctness. The results show that deep learning approaches outperform conventional techniques in both decreased and full resolution circumstances, with the PRACS algorithm taking the top spot overall. In conclusion, deep learning shows potential for improving pan-sharpening, although conventional approaches remain competitive. Comprehensive benchmarking informs the best choice for high-fidelity fusion according to application needs.

IV.METHODOLOGY

To account for variability, this study will use a collection of matched panchromatic and multispectral satellite picture pairings from different geographic locations and seasons. All the data collected are from secondary sources [4]. Ten advanced stage deep learning-based super-resolution approaches will be developed, trained, and tested on panchromatic pictures, including methods like feedback networks for image super- resolution (SRFBN). Quantitative analysis will evaluate test data performance parameters such as peak signal-to-noise ratio, structural similarity index, and edge reconstructions quality. Additionally, ocular assessment will evaluate spatial detail and clarity improvement. The best performing super- resolution algorithm will be chosen and integrated into a standard pansharpening workflow, which will fuse the super- resolved panchromatic visuals with the native multispectral information using an established pansharpening method, such as the addition wavelet luminance proportional technique. A similar quantitative study and visual evaluation will be conducted to compare both the spatial spectrum quality of traditional pansharpening outputs to those that use the super- resolution initial processing phase [5]. Case studies will show how the suggested 5technique works on real-world data from several application areas with different geographical features and resolution requirements.

V. RESULTS AND ANALYSIS

A. Reduced Resolution Experiments

Pan-sharpening combines a high spatial resolution panchromatic (PAN) picture with a high spectral resolution multi-spectral (MS) image to produce an integrated product with improved spatial and spectral properties. Since the real sharpened output is not accessible for reference, the Wald approach creates both training and assessment datasets. It initially replicates lower-quality photography by downsampling the MS data compared to the PAN based on their resolution ratio. The decreased MS bands are upsampled back to their original proportions. The simulated MS and the original downsampled PAN band register as a 5-band input stack, with the possibility of supplementing input cues with spectral indices such as the Normalized Difference Vegetation Index (NDVI) or Water Index (NDWI) [6]. The original MS wristbands serve as references objectives during supervised training. This generates a simulated input-target pair with reduced resolutions while keeping the original data for ultimate benchmarking. The trained model provides a full resolution pan-sharpened integration based on the arrangement and connections learnt from the smaller surrogate sets. In addition to measurements, visual assessments of color presentation and object sharpness are significant for determining pan-sharpening quality in relation to human perception [7]. Three lower resolution picture patches representing industrial, agricultural/vegetated, and heterogeneous mixed land cover were chosen for statistical and visual analysis. The spectral correlation coefficient (CC) measure compared each band of the sharpened outputs to the original multispectral reference data. CC is a useful tool for assessing bias. Visually, older techniques injected spatial information well onto industrial roofs, but deep learning methods better preserved the original multispectral hues and characteristics. Deep learning with L2 loss exhibited some blurring compared to L1 approaches [8]. Removing spectral indices also in- creased color realism. CC correlations demonstrated a greater agreement between deep learning outputs and reference data than conventional approaches across all bands. This highlights deep learning's ability to increase color retention and feature sharpness while preserving excellent spectral integrity. Both quantitative data and qualitative visualization are required for a full pan-sharpening performance assessment that aligns with application requirements.

Networks	*Learning Rate*	*Epochs*	*Optimizers*
PNN indices L1	0.001	100	SGD
PNN indices L2	0.001	300	SGD
PNN nonindices L1	0.001	200	SGD
PNN nonindices L2	0.001	300	SGD
PSGAN L1	0.0002	200	Adam
PSGAN L1	0.0002	50	Adam

VI.CONCLUSION

This investigation looked into pan-sharpening technologies ranging from older methods like component replacement and spectrum index injections to more contemporary deep learning-based techniques. A comparative analysis of a range of picture pairings shown that standard techniques may efficiently inject spatial information from panchromatic data into multispectral bands. However, some color distortions and spectral fidelity loss do occur. In contrast, the most recent convolutional and generating adversarial neural network designs show significant advances in keeping original spectral fingerprints and color representations while dramatically increasing resolution. Quantitative quality measurements combined with visual representation provide complete performance benchmarking based on end-use goals. Though machine and deep learning requires more computing complexity, developments in GPU processing mitigate this. Deep learning-based pan-sharpening offers enormous potential in terms of optimizing the spatial resolution and quality of color without losing spectral content accuracy. The field will continue to innovate as sensor and computing power coevolve. Overall, this research recommends the right choice and execution of pan-sharpening techniques depending on the application needs for high quality merged Earth observation data.

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