International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 1
***Article Received:** 10 November 2022 **Revised:** 14 December 2022 **Accepted:** 30 December 2022*

Colorization of Multispectral Image Fusion using Convolutional Neural Network approach

Mitul M. Patel
Department of Electronics and Communication Engineering
Parul Institute of Engineering and Technology, Parul University
Vadodara, India
patelmitul4388@gmail.com

Arvind R. Yadav
Department of Electronics and Communication Engineering
Parul Institute of Engineering and Technology, Parul University
Vadodara, India
arvind.yadav.me@gmail.com

Abstract— The proposed technique offers a significant advantage in enhancing multiband nighttime imagery for surveillance and navigation purposes., The multi-band image data set comprises visual and infrared motion sequences with various military and civilian surveillance scenarios which include people that are stationary, walking or running, Vehicles and buildings or other man-made structures. Colorization method led to provide superior discrimination, identification of objects (Lesions), faster reaction times and an increased scene understanding than monochrome fused image. The guided filtering approach is used to decompose the source images hence they are divided into two parts: approximation part and detail content part further the weighted-averaging method is used to fuse the approximation part. The multi-layer features are extracted from the detail content part using the VGG-19 network. Finally, the approximation part and detail content part will be combined to reconstruct the fused image. The proposed approach has offers better outcomes equated to prevailing state-of-the-art techniques in terms of quantitative and qualitative parameters. In future, propose technique will help Battlefield monitoring, Defence for situation awareness, Surveillance, Target tracking and Person authentication.

Keywords-multisensory image; image fusion; VGG-19; LAB model; colorization; CNN.

I. INTRODUCTION

Thermal radiation occurs when object emit electromagnetic waves of varying frequency under normal circumstances, which is called thermal radiation. It is difficult have to see thermal radiation information using human eye so that different sensors are required to process the infrared image and acquire its thermal radiation information, which has strong target identification abilities. The information obtained using visible light sensors is richer, scene details and textures are apparent, and spatial resolution is great. A nighttime setting might make it harder to extract image information from Infrared (IR) or Visible (VIS) images. The most challenging aspect in the image fusion is to extracting significant features from various type of input images and merging to create a fused image.

In recent years, an increasing variety of image techniques employing have been formed. To selecting the most important parts from the different modality images and incorporating them into the fusion is now one of the most preferred approaches for creating a fused image while the visible image's texture complexity is considered by edges and gradients. Selection of manually developed fusion rules to represent a fused image will result in lack of variety of retrieved features and artifacts, depending on the source image's imaging mechanism. In addition, manual fusion criteria for multi-source image fusion will make the process more difficult. Using the image fusion strategy based on deep learning, an adaptive mechanism might be employed to supply weights to the model. This method significantly decreases the computation cost, which is essential in many fusion rules, when compared to the design rules of older methods. We describe a multi spectral image fusion technique. To break down a source image into its basic components, image decomposition is performed, and the fused approximation part is produced using a weighted average method. The next step is to calculate multi-layer features using a deep-learning algorithm. To retain the more information each layer's features are weighted using the soft-max operator to produce a proposed fused detail content. The same procedure applied to a number of layers; we will have a number of candidates for the fuse image. The max selection technique forms the final fused detail image, the approximation components and detail contents are combined to reconstruct the fused image.

The organization of this manuscript is as follows, literature survey which presents the how to apply deep learning concept in image fusion method and colorization of fused image described in section II. State of art of image fusion methods are discussed in section III. Multispectral image fusion using VGG-19 technique is conversed in section IV. The experimental outcomes with detail analysis and comparison of various image fusion approaches are shown in section V. Colorization of fused image with the help of ground truth color image is described in section VI. Finally, conclusion and future scope of the paper are mentioned.

II. Related work

Z. Ping and et al. [17] used a mixed information decomposition scheme (MID). Texture detail layers, edge layers, and a foundation layer were created from the original image. Texture details and edges are combined using selection of perceptual parameters, while the base layer and its detail levels are combined using sparse representation. It's possible that the fused layers can reconstitute the combined image.

Xingchen Zhang and et al. [28] represented the visible and infrared image fusion benchmark (VIFB) which is a collection of image pairs (21), code library with various fusion algorithms (20), and assessment parameters (13) that outlines current developments in fusion of visible and infrared images. Authors also run extensive tests to understand the performance of different methods. Through the examination of qualitative and quantitative data, author proposed plausible approaches for image fusion, as well as some insights on the current state and future images.

Hui Li, and et al. [8] discussed the network and spatial/channel attention models based on nest connections which are used to merge infrared as well as visible images. By using multi-scale perspective, the nest connection-based network is capable of retaining an immense quantity of information from the input. Author used three main components decoder, fusion method, and an encoder in proposed fusion method.

Liu, Yu and et al. [14] used the Convolutional Sparse Representation (CSR) approach for fused the images. CSR model has two disadvantages; it is able to overcome them. JSRD method of multi focus and multi modal image fusion is proposed with the CSR framework.

Ma, Jinlei and et al. [15] represented that to design a multi-scale strategy that tackles numerous prominent disadvantages associated with existing methods, VSM and weighted least square optimization were used together using multiscale decomposition, split images into basic and detail layers using a rolling guidance filter (RGF) and a Gaussian filter (MSD). In contrast to traditional MSDs, this MSD reduces halos at the margins, while preserving the information of certain scales. There is also the issue of low residual frequency being present in the base layers of most MSDs, and traditional "averaging" fusion schemes do not work well. One solution for this is to fuse the basic layers with a new, more efficient VSM-based method as a final step, we offer a unique WLS optimization technique for merging the detail more visual features and less noise are transferred into the merged image through this technique.

Shreyamsha Kumar and et al. [6] suggested that source images be fused using a weighted average derived for extraction methods. Visually and statistically, multisensory and multifocal images were used to form the input photos, global and local saliency maps were created.

F.G. Veshki and et al. [22] represented generated input images, the JSR method is used to build global and local saliency maps. The researchers then suggested a saliency detection method that merges global and local saliency maps into a single saliency map.

Toet and et al. [21] compared the ability of humans to identify scenes using monochrome intensified (II) and long wave infrared images, as well as color daylight and fused multispectral images. As a result of their research, they found the highest accuracy and remembrance metrics, while II and IR photography produced significantly lower metrics.

Wan, Shaohua and et al. [23] used neural networks and optimization method to offer a fully automated grayscale image colorization technique. It divides grayscale image into super pixels and extracts features of particular locations of interest in each super pixel using a predetermined training set that includes grayscale images and their matching color images. Author also suggested fusion using Joint Sparse Representations and Coupled Dictionary Learning approach and to propagate the color points to nearby pixels in order to improve the picture colorization outcomes.

Zeger, Ivana and et al. [26] presented image approaches. A taxonomy of relevant approaches is provided, as well as an explanation of the underlying concepts and an analysis of their merits and limitations. In particular, deep learning techniques are emphasized when it comes to automated conversion, deep learning colorization approaches beat other methods in both quality and speed.

Limmer, Matthias and et al. [12] was founded that the RGB color spectrum can be converted another CNN images. To accomplish it is necessary to impart a direct and integrated images with a life like appearance can be produced by the trained model without the need for any user instruction or a reference image library during the recall phase. To preserve the rich details, NIR image's high frequency characteristics are translated to the approximated RGB image. The high frequency characteristics of the NIR image are transferred to the approximated RGB image in order to maintain the rich details. To train and assess the given method, it was used a real-world dataset including a significant number of road scene images.

Li, Bo and et al. [7] presented Colorization results which are more resilient and higher-quality when textures are matched across scales, according to the proposed method. Consideration is given to local match-up scales that will be merged with the use of a global optimization technique that reduces both match-up mistakes. Author solved the minimization problem more efficiently by using a multi-label graph. This can be result in the sky appearing above a meadow because only low-level texture elements are used.

Zheng, Yufeng and et al. [14] included well-known color mapping methods that rely on statistical matching, as well as newly-introduced color transferring methods that rely on convolutional neural networks (CNNs) to map colors. To comparing colorization outcomes is done quantitatively using the Objective Evaluation Index (OEI). As a consequence of these experiments, the color transferring methods utilizing CNN appear to be highly promising for colorizing.

Hamam, Tomer and et al. [4] presented the unique texture-based technique, which offer a new way for automatically coloring as a starting point, the technique employs a reference (source) color image, which was chosen from a database of natural sceneries. In order to choose the source image, a texture-matching algorithm compared with the IR image. Every IR segment in the source and target images is split into texture-based segments, which are then compared to find the optimal color section where IR-color segments were colored, global and local characteristics are taken into account. To compare to previous methods, authors found that ours creates images that look more natural.

Zhang, Weiwen and et al. [27] has proposed method for image segmentation, it first uses semantic segmentation, and then categorizes and colors the image to prevent reusing the

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 1
***Article Received:** 10 November 2022 **Revised:** 14 December 2022 **Accepted:** 30 December 2022*

same color scheme and unusual hues. Author used a single lookup table for global colorization [30][31].

III. STATE-OF-THE-ART OF IMAGE FUSION METHODS

An infrared and visible image-fusion technique is presented as a result of prior research. Deep learning techniques are increasingly being used to merge infrared and visible images. These cutting-edge techniques may be used for image pre-processing, target identification, and classification to name a few applications.

A. JSR (Joint Sparse Representations)

Source images are separated into complimentary sub-images and a redundant sub-image using joint sparse representation. It doesn't matter if two complementing sub-images are redundant if we wish to integrate them [13] [32][33].

B. JSRSD (Joint Sparse Representation saliency detection)

Each colour channel is represented using a sparse coding technique based on a learnt lexicon of patches from natural images. The saliency of each patch is then calculated using both global and local saliencies, which are then combined to produce the saliency for every patch [10]. A patch's local saliency can be determined by separating it from its surroundings. The rarity of a patch in comparison to all other patches in an image determines its global saliency. This final saliency map combines all colour channels' local and global saliency map.

C. CBF (Cross Bilateral Filter)

Multimodal images are being used in a wider range of fields as the variety of imaging methods increases [6]. As a result of this, multimodal images are sometimes contaminated. Using a Cross Bilateral Filter (CBF), two multimodal images polluted by noise can be de-noised simultaneously [34][35].

D. WLS (Weighted Least Square)

The weight map is optimised using the Weighted Least Squares (WLS) optimization framework [15]. Color saturation measurements and texture features are perfect for quickly constructing weight maps to regulate the contribution from an input set of an auto exposure images.

E. ConvSR (convolutional sparse representation model)

Multiple images can be combined by using a CSR-based framework that separates multiple layers [14]. In terms of objective evaluation and visual quality, experiments have proven that the suggested fusion methods outperform SR-based methods.

IV. METHODOLOGY

Colorization of multispectral image fusion is performed in two sections in this paper. The first section uses a deep learning VGG-19 network to mix input images (visible and infrared) and create primary weight maps. A soft-max operator used to obtain the absolute weight maps. For each weight map and detail content components, the first fused detail content component is formed. The fused detail content component is reconstructed using the max operator then fused approximation component and fused detail content part are added to generate resultant fused image.

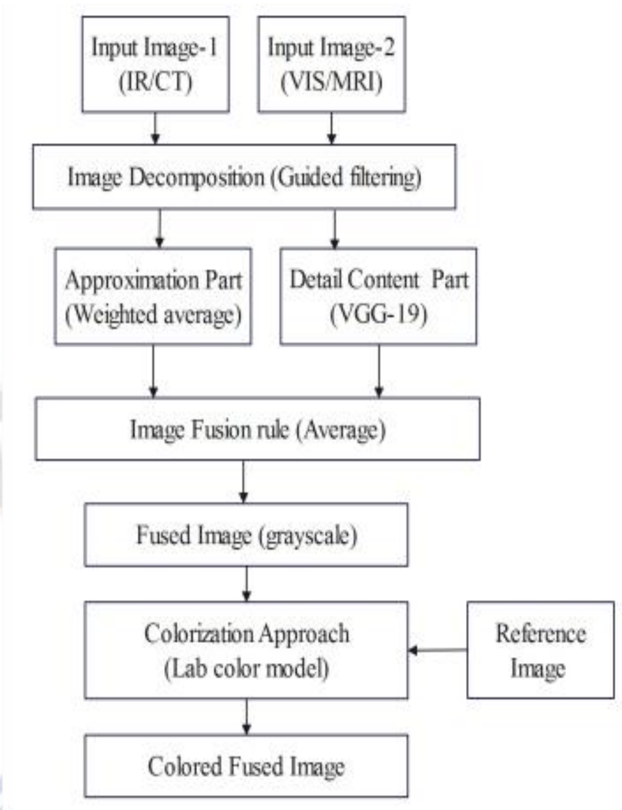


Figure 1. Proposed methodology of multispectral Image fusion with colorization.

The results of VGG-19 are compared with existing image fusion approaches in Table 1and Figure-5. Figure-7 shows how the color information transferred from the reference image (colored image) to resulting grayscale fused image [36][37][38][39].

A. VGG 19 based Image fusion

There is a total of K input images that have been pre-registered. We consider K = 2 in these experiments, however the fusion technique is the same for $K > 2$. You can find the IK where K = 1, 2 for input images. The optimization method is more effective than wavelet-based image decomposition and low-rank latent analysis [24, 25]. For every input image IK, the approximation part (base part) I_{Kb} and detail content part I_{Kd} are gained unglued by [9].

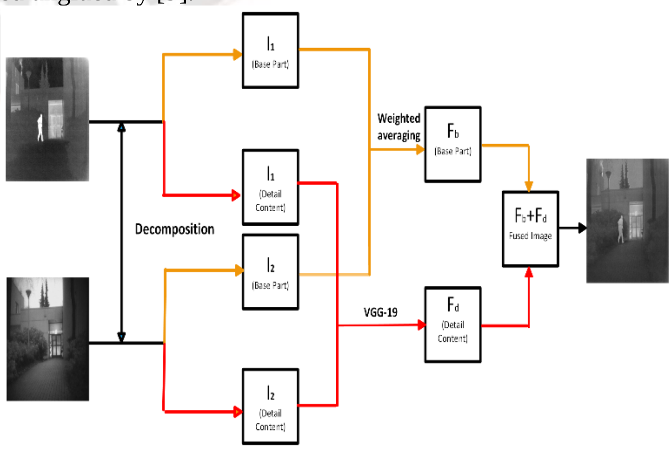


Figure 2. Frame Work of VGG 19 based Image Fusion.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 1
***Article Received:** 10 November 2022 **Revised:** 14 December 2022 **Accepted:** 30 December 2022*

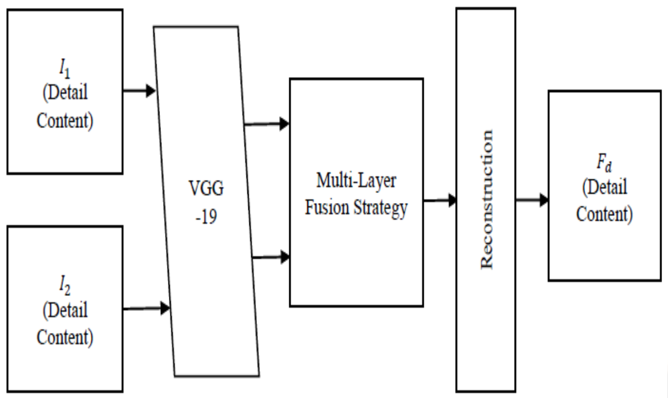


Figure 3. Frame Work of detail content part using VGG 19.

The approximation part is fused using a weighted averaging method and the detail content part is recreated using VGG-19 which is shown in Figure 3. The summary of deep learning-based image fusion process is mentation as below:

Approximation part Fusion: Basic features and redundant information can be found in approximation part extracted from source images. To combine approximation elements, it was decided to utilize a weighted-averaging technique. For this experiment each approximation part has a weight value of 0.5.

Detail Content Part Fusion: Detail features are taken out by a VGG-19 network for detail-oriented fusion.

Reconstruction: Equation (1) is usage to generate the final fused image, which is made up of fused approximation parts F_B and fused detail content parts F_D.

$$F(i, j) = F_B(i, j) + F_D(i, j) \ldots\ldots\ldots\ldots\ldots (1)$$

V. EXPERIMENT RESULT AND ANALYSIS

The datasets for this experiment are taken from [8] and [20]. Some of the samples are shown in Figure 4. In Figure.4 first column CT scan image represent the bony structures and MRI image provides details regarding brain tissue anatomy [1, 2 and 5]. The remaining three column, pair of sample source images are represented like. Soldier in Smoke 1, Sandpath and Kaptein_1123. In first pair (Soldier in Smoke 1) soldier with gun visible in infrared image while smoke appear in visible image [20]. The second pair (sandpath) consists of a sand path and wire fencing that may be seen in visible and infrared images to locate a person buried beneath the forest. The background, illumination, and object near the door are all clearly visible in the third image pair (Kaptein 1123). IR image shows that smoke emanating from the chamber and a person walking in the opposite direction.

Figure 4. Sample of Multisensory input images.

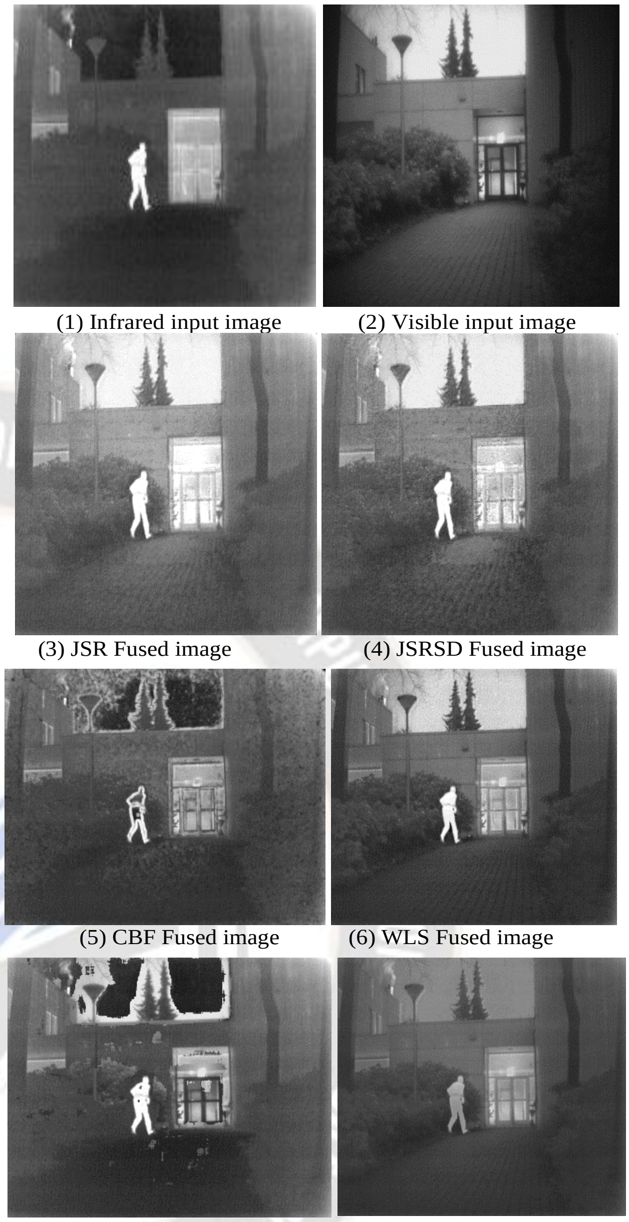


Figure 5. (1) Infrared input image (2) Visible input image (3) JSR Fused image (4) JSRSD Fused image (5) CBF Fused image (6) WLS Fused image (7) ConvSR Fused image and (8) VGG-19 Fused image.

In Figure 5 (5) CBF based Fused image and (7) ConvSR based Fused image have more extra patches and objects are blurred. In JSR Fused image (3) objects around door are not clearly visible. JSRSD Fused image (4) and WLS Fused image (6) having not clear background compared VGG-19 Fused image (8). VGG-19 Fused image (8) have good visual image quality and look more natural.

Entropy measures how much information is available in to a fused image from input images. Using mutual information (MI) shows that the quantity of information transferred into a fused image. Q_{ABF} is an index of edge information preservation. FMI dct and FMI w compute related information during discrete cosine and wavelet transform respectively [3]. SCD indicates the sum of correlations of differences (SCD). The capacity to retain structural information quantity by SSIM. The larger the value of all parameters (except Nabf) represent the better the fused image

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 1
***Article Received:** 10 November 2022 **Revised:** 14 December 2022 **Accepted:** 30 December 2022*

quality. NABF indicates the noise or artifacts that have been added due to image fusion so its small value indicates good image fusion. The better value of the parameters is highlighted in Table 1.

TABLE 1 COMPARISON OF ALL IMAGE FUSION METHODS WITH AVERAGE VALUE OF VISIBLE AND INFRARED IMAGES.

Method	EN	MI	Qabf	FMI pixel	FMI_dct	FMI_w	Nabf	SCD	SSIM
JSR	6.36	12.72	0.35	0.88	0.16	0.20	0.23	**1.75**	0.60
JSRSD	6.69	13.38	0.32	0.86	0.14	0.18	0.35	1.59	0.54
CBF	6.85	13.71	0.44	0.87	0.26	0.32	0.31	1.39	0.60
WLS	6.63	13.27	0.52	0.90	0.33	0.38	0.22	1.78	0.71
ConvSR	**7.08**	**14.17**	**0.60**	0.89	0.17	0.38	0.06	1.14	0.66
VGG-19	6.18	12.36	0.36	**0.91**	**0.40**	**0.41**	**0.01**	1.63	**0.77**

The VGG-19 technique has larger values of FMI pixel, FMI dct, FMI w and SSIM indicating that additional details was conveyed from the original images to the fused image. VGG-19 give the smaller value of Nabf that represent the smaller number of artifacts generated in fused image during image fusion. There are pair of 21 source images (VIS image and IR image) are used for comparison and available at [20].

VI. COLORIZATION APPROACH

In the colorization process, color information is transferred from the reference color image to the fusion output (fused image).

Figure 6. Proposed algorithm for colorization

The two source images should have a significant quality content association in order to achieve appropriate colorization. The CNN Network used to pinpoint a pixel in the reference image for each pixel in the fused image. The Lab color model is meant to be more accurate in replicating human vision than the RGB color space, as well as more convenient for color adjustment. Color prediction needs a pixel-by-pixel and semantic-by-semantic knowledge of an image. The value of single pixel luminance has been proven to limit the likely color of that pixel in natural image statistics. More saturated colors are associated with the darkest brightness levels [15]. The different feature are extracted using Gabor filter, Dense SIFT and CNN, The turbo super pixels used for Super pixel extraction, Classification and identification of the object performed on both input images. Color transfer based on closed and average super pixels [11,29].

A. Network architecture

A complete list of the layers that are implemented as following levels in a feed-forward network mentation in Table 2. Where M is the output spatial resolution, number of channels is N, stride ratio is S, D is the kernel dilation and Sa is the total stride across all layers [16]. The layer's effective dilatation in relation to the input, L if a 1x1 convolution and cross-entropy loss layer was applied, B_N whether a Batch Norm layer was employed following layer.

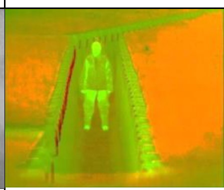
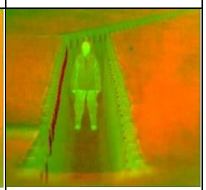
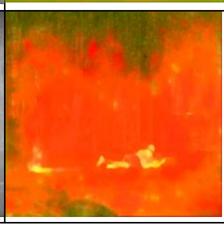
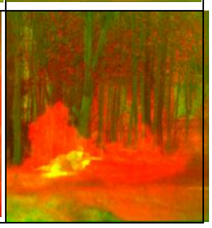
TABLE 2 NETWORK ARCHITECTURE WITH PARAMETERS.

Layer	M	N	S	D	S_a	D_e	BN	L
Conv 1.1	450	64	1	1	1	1	N	N
Conv 1.2	225	64	2	1	1	1	Y	N
Conv 2.1	225	128	1	1	2	2	N	N
Conv 2.2	112	128	2	1	2	2	Y	N
Conv 3.1	112	256	1	1	4	4	N	N
Conv 3.2	112	256	1	1	4	4	N	N
Conv 3.3	56	256	2	1	4	4	Y	N
Conv 4.1	56	512	1	1	8	8	N	N
Conv 4.2	56	512	1	1	8	8	N	N
Conv 4.3	56	512	1	1	8	8	Y	N
Conv 5.1	56	512	1	2	8	16	N	N
Conv 5.2	56	512	1	2	8	16	N	N
Conv 5.3	56	512	1	2	8	16	Y	N
Conv 6.1	56	512	1	2	8	16	N	N
Conv 6.2	56	512	1	2	8	16	N	N
Conv 6.3	56	512	1	2	8	16	Y	N
Conv 7.1	56	256	1	1	8	8	N	N
Conv 7.2	56	256	1	1	8	8	N	N
Conv 7.3	56	256	1	1	8	8	Y	N
Conv 8.1	112	128	0.5	1	4	4	N	N
Conv 8.2	112	128	1	1	4	4	N	N
Conv 8.3	112	128	1	1	4	4	N	Y

Y indicates that the Batch Norm layer was used, as well as 1x1 convolution and cross-entropy loss layers, while N indicates that no layer was used. Down sampling is indicated by stride(S) values larger than 1, whereas up sampling is indicated by stride(S) values less than 1.

B. Objective Function

To mapping the color channel's objective function is used in CIE Lab color space and define as $\hat{Y} = F(X)$ Where, X: Input lightness channel $X\epsilon RHXWX1$ and Y: $X\epsilon RHXWX2$ two connected color channels.

	Fused Image (VGG-19 network)	Ground Truth	Colorization Image
Soldier in Trench			
Soldier in Smoke			

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 1
***Article Received:** 10 November 2022 **Revised:** 14 December 2022 **Accepted:** 30 December 2022*

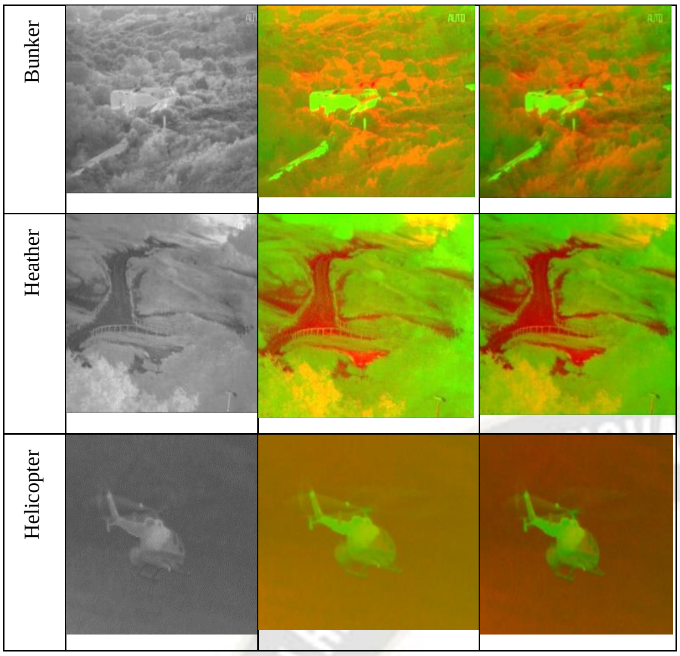


Figure 7. Output of colorization approach and compare with ground truth.

The images depicted in figure 7 show the results of the colorization. Here, five colored images i.e. Soldier in trench, Soldier in Smoke, Bunker, Heather and Helicopter are formed using the combination of fused images and reference images. In the first input image i.e. Soldier in trench, soldier was in trench but it was difficult to recognize the scenario. After applying colorization approach, it is clearly recognizable that warrior was in trench along with its path boundary. When considering 2nd image, i.e. Soldier in Smoke, soldier was in lying positing and is surrounded by the smoky environment in the forest. It is further noted that background scene and smoke are completely mixed-up and hard to differentiate the smoky surroundings with trees. Using the applied methodology, it becomes easy to differentiate all the three mentioned aspects i.e. Soldier with gun, Smoke environment and forest. In the 3rd image i.e. Bunker, bunker location is not clearly identifiable by wireless sensors [17, 18 and 19] because its color is mixed-up with surrounding trees. Once the suitable reference image is used following-up by the applied methodology, bunker location is clearly detectable. Same way, in the 4th image and 5th image, i.e. Heather and Helicopter, the resultant images are improved and interested objects are clearly distinguishable i.e. fences in the 4th image and aerial vehicle in the 5th image.

VII. CONCLUSION

In this work, fusion of nighttime imagery from two different modalities namely IR and visible has been implemented. These images have been decomposed using guided filtering in to approximation and detail part. Further the approximation part of IR and visible image has been processed using weighted average filtering approach and the detailed part of IR and visible image has been processed using VGG-19. The result obtained by VGG-19 and weighted averaging approach has been fused using average fusion rule. The result obtained by proposed fusion approach is found to be better fused image, compared to the existing approaches of IR and visible images fusion process. In compared to the state-of-the-art, VGG-19 technique offers improved results in terms of quantitative and qualitative parameters. The efficiency of the proposed approach has been evaluated using nine evaluation parameters. Further to enhance feature discrimination value of fused image it has been colorize using LAB model. Colorization of fused images are closer and indistinguishable from ground truth images with the help of CNN and select the appropriate objective function. In future the proposed model shall be evaluated for fusion of multi focus and multi temporal images helpful to medical professional for diagnoses of various disease.

REFERENCES

[1] N. Alseelawi, H.T. Hazim, S. ALRikabi, H.TH, A Novel Method of Multimodal Medical Image Fusion Based on Hybrid Approach of NSCT and DTCWT, International Journal of Online & Biomedical Engineering, 18(3):114-133, 2022.

[2] X.W. Bo, H.X. Xu, D. Wang, L.H. Guo, L.P. Sun, X.L. Li, C.K. Zhao, Y.P. He, B.J. Liu, D.D. Li, K. Zhang, Fusion imaging of contrast-enhanced ultrasound and contrast-enhanced CT or MRI before radio frequency ablation for liver cancers, The British Journal of Radiology, 89(1067): 20160379, 2016.

[3] M. Haghighat, M.A. Razian, Fast-FMI: Non-reference image fusion metric, In 2014 IEEE 8th International Conference on Application of Information and Communication Technologies (AICT):1-3, 2014.

[4] T. Hamam, Y. Dordek, D. Cohen, Single-band infrared texture-based image colorization, In 2012 IEEE 27th Convention of Electrical and Electronics Engineers in Israel: 1-5 2012.

[5] S.H. Huang, C.Y. Chien, W.C. Lin, F.M. Fang, P.W. Wang, C.C. Lui, Y.C. Huang, B.T. Hung, M.C. Tu, C.C. Chang, A comparative study of fused FDG PET/MRI, PET/CT, MRI, and CT imaging for assessing surrounding tissue invasion of advanced buccal squamous cell carcinoma, Clinical nuclear medicine, 36(7): 518-525, 2011.

[6] B.K. Shreyamsha Kumar, Multifocus and multispectral image fusion based on pixel significance using discrete cosine harmonic wavelet transform, Signal, Image and Video Processing, 7: 1125-1143, 2013.

[7] B. Li, Y.K. Lai, M. John, P.L. Rosin, Automatic example-based image colorization using location-aware cross-scale matching, IEEE Transactions on Image Processing, 28(9): 4606-4619, 2019.

[8] H. Li, X.J. Wu, J. Kittler, August, Infrared and visible image fusion using a deep learning framework, In 2018 24th international conference on pattern recognition (ICPR): 2705-2710, 2018.

[9] S. Li, X. Kang, J. Hu, Image fusion with guided filtering, IEEE Transactions on Image processing, 22(7): 2864-2875, 2013.

[10] Y. Li, J. Zhao, Z. Lv, J. Li, Medical image fusion method by deep learning, International Journal of Cognitive Computing in Engineering, 2:21-29, 2021.

[11] Y. Li, J. Zhao, Z. Lv, Z. Pan, Multimodal medical supervised image fusion method by CNN, Frontiers in Neuroscience, 15:638976, 2021.

[12] M. Limmer, H.P. Lensch, Infrared colorization using deep convolutional neural networks, In 2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA):61-68, 2016.

[13] C.H. Liu, Y. Qi, W.R. Ding, Infrared and visible image fusion method based on saliency detection in sparse domain, Infrared Physics & Technology, 83:94-102, 2017.

[14] Y. Liu, X. Chen, R.K. Ward, Z.J. Wang, Image fusion with convolutional sparse representation, IEEE signal processing letters, 23(12):1882-1886, 2016.

[15] J. Ma, Z. Zhou, B. Wang, H. Zong, Infrared and visible image fusion based on visual saliency map and weighted least

square optimization, Infrared Physics & Technology, 82:8-17, 2017.

[16] J.P.B. O'connor, P.S. Tofts, K.A. Miles, L.M. Parkes, G. Thompson, A. Jackson, Dynamic contrast-enhanced imaging techniques: CT and MRI, The British journal of radiology, 84(2), :112-S120, 2011.

[17] Z. Ping, J. Shi, Z. Zhang, Z. Yue, C. Rong, Infrared and Visible Image Fusion and Image Quality Evaluation, In 2020 12th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), 1:175-179, 2020.

[18] B. Rajalingam, R. Priya, Multimodal medical image fusion based on deep learning neural network for clinical treatment analysis, International Journal of ChemTech Research, 11(06), :160-176, 2018.

[19] N. Salankar, D. Koundal, C. Chakraborty, L. Garg, Automated attention deficit classification system from multimodal physiological signals, Multimedia Tools and Applications, 82(4):4897-4912, 2023.

[20] A. Toet, TNO image fusion dataset, Figshare. Dataset. https://figshare.com/articles/TNO Image Fusion Dataset/1008029, 2014.

[21] A. Toet, M.J. de Jong, M.A. Hogervorst, I.T. Hooge, Perceptual evaluation of colorized nighttime imagery, In Human Vision and Electronic Imaging XIX, 9014:276-289, 2014.

[22] F.G. Veshki, N. Ouzir, S.A. Vorobyov, Image fusion using joint sparse representations and coupled dictionary learning, In IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP): 8344-8348, 2020.

[23] S. Wan, Y. Xia, L. Qi, Y.H. Yang, M. Atiquzzaman, Automated colorization of a grayscale image with seed points propagation, IEEE Transactions on Multimedia, 22(7): 1756-1768, 2020.

[24] Y. Wu, H. Guo, C. Chakraborty, M. Khosravi, S. Berretti, S. Wan, Edge computing driven low-light image dynamic enhancement for object detection, IEEE Transactions on Network Science and Engineering, 2022.

[25] Xu, Y. Wang, X. Zhang, N. Zhang, S. Yu, Infrared and visible image fusion using a deep unsupervised framework with perceptual loss, IEEE Access, 8: 206445-206458, 2020.

[26] Žeger, S. Grgić, An overview of grayscale image colorization methods, In 2020 International Symposium ELMAR: 109-112, 2020.

[27] W. Zhang, X. Gu, X. Gu, Method for Coloring Night-vision Imagery Based on Multispectral Semantic Segmentation, In 2018 Australian & New Zealand Control Conference (ANZCC):1-6, 2018.

[28] X. Zhang, P. Ye, G. Xiao, VIFB: A visible and infrared image fusion benchmark, In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops: 104-105, 2020.

[29] Y. Zheng, E.P. Blasch, Night Vision Colorization from Color Mapping to Color Transferring, In 2019 22th International Conference on Information Fusion (FUSION): 1-7, 2019.

[30] Mall, P. K., et al. "A comprehensive review of deep neural networks for medical image processing: Recent developments and future opportunities. Healthcare Analytics, 4, 100216." (2023).

[31] Narayan, Vipul, et al. "Severity of Lumpy Disease detection based on Deep Learning Technique." *2023 International Conference on Disruptive Technologies (ICDT)*. IEEE, 2023.

[32] Narayan, Vipul, et al. "A Comprehensive Review of Various Approach for Medical Image Segmentation and Disease Prediction." *Wireless Personal Communications* 132.3 (2023): 1819-1848.

[33] Mall, Pawan Kumar, et al. "Rank Based Two Stage Semi-Supervised Deep Learning Model for X-Ray Images Classification: AN APPROACH TOWARD TAGGING UNLABELED MEDICAL DATASET." *Journal of Scientific & Industrial Research (JSIR)* 82.08 (2023): 818-830.

[34] Saxena, Aditya, et al. "Comparative Analysis Of AI Regression And Classification Models For Predicting House Damages İn Nepal: Proposed Architectures And Techniques." *Journal of Pharmaceutical Negative Results* (2022): 6203-6215.

[35] Kumar, Vaibhav, et al. "A Machine Learning Approach For Predicting Onset And Progression"“Towards Early Detection Of Chronic Diseases “." *Journal of Pharmaceutical Negative Results* (2022): 6195-6202.

[36] Chaturvedi, Pooja, A. K. Daniel, and Vipul Narayan. "A Novel Heuristic for Maximizing Lifetime of Target Coverage in Wireless Sensor Networks." *Advanced Wireless Communication and Sensor Networks*. Chapman and Hall/CRC 227-242.

[37] Kumar, Vaibhav, et al. "A Machine Learning Approach For Predicting Onset And Progression"“Towards Early Detection Of Chronic Diseases “." *Journal of Pharmaceutical Negative Results* (2022): 6195-6202.

[38] Narayan, Vipul, et al. "7 Extracting business methodology: using artificial intelligence-based method." *Semantic Intelligent Computing and Applications* 16 (2023): 123.

[39] Mall, Pawan Kumar, et al. "A comprehensive review of deep neural networks for medical image processing: Recent developments and future opportunities." *Healthcare Analytics* (2023): 100216.