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MMIF-NET: MULTI MODEL IMAGE FUSION USING DEEP LEARNING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Image fusion plays a major role in many computer vision applications. However, the conventional image processing methods were failed to perform the fusion operation. Therefore, this work focused on the development of multi model image fusion network (MMIF-Net) using deep learning convolutional neural network (DLCNN). Initially, preprocessing operation is carried out using median filter, which removes the different types of noises from source MRI and CT images. Then, pixel-specific features were extracted using DLCNN model, which performed the feature-specific content-based fusion. Here, the DLCNN is used to extract the probabilities of principal component analysis in each MRI, CT region. Then, the post-processing operation is implemented using Gaussian filter, which enhanced the overall texture, spatial, spectral regions of MRI, CT images. The simulation results show that the proposed method resulted in optimal performance than the conventional image fusion methods.

Keywords: multi model image fusion network, deep learning convolutional neural network, median filter, gaussian filter.

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1. INTRODUCTION

Humans possess a remarkable sense to perceive visuals. Eye supports uncountable human activities [1]. The image acquisition of a visual transfer substantially supplemental data than other specifications attached to the scene. Humans possess five sensing potentials namely eyes (sight), ears (sound), nose (smell), tongue (taste), and skin (sensory) with a capability of capturing independent data. All of these systems transmit signals to the brain where the data is finally collected or fused which later leads to the interpretation of a scenario [2]. The decision-making abilities and execution of tasks rely on this captured data. Data fusion is a mechanism that merges data from various sources for adequate or condensed delineation of enormous information for making a supporting limb for description and decision-making capabilities [3]. One classic example of a data fusion system is the human brain. Let us take an example of an eye as a sensor. The biological sensor extracts important attributes of a segment by a glance of a scenario more than once [4]. The Human brain integrates the visual signals from the eye and provides the details concealed in a singular view. Multiple views enhance the decision making; therefore, we are not satisfied with a single image of a snap shot derived from a digital camera which leads to multiple shots for better clarity and precision [5]. It is a fact that not any images comprise the desired standard. Usually, the constructive features of these must be amalgamated to obtain the appropriate image. The process pushes us to fuse the image for an optimal gain. Various cameras can be used for fusing images [6]. The definition of image fusion is as follows, "image fusion is the process of merging or combining or integrating useful or complementary information of several source images such that the resultant image provides more accurate description about the scene than any one of the individual source images" [7]. As medical care continues to progress, an ever-increasing number of people are making use of an ever-expanding variety of cutting-edge imaging technologies. CT, MR-Gad, and MR-T2 are the primary forms of medical imaging that are used most often in clinical settings. In addition to that, it also consists of certain standard RGB images, such as SPECT or PET images [8]. The information included in medical images may be very beneficial. It has increasingly become the primary foundation for clinical diagnosis for clinicians to evaluate patients based on CT scans and other medical images. These evaluations are performed in order to determine the state of the patient [9]. As a result of this, the area of computer vision research that focuses on medical image processing has emerged as the centre of interest in recent years. The process of medical image analysis cannot proceed without the segmentation of medical images. The accurate segmentation of medical images gives information that may be particularly helpful for computer-assisted diagnosis and treatment of illnesses in general, as well as cancer in particular [10]. However, standard image processing techniques were incapable of performing the fusion process.

- The emphasis of this effort was on developing MMIF-Net utilising DLCNN.

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- Initial preprocessing is performed using a median filter, which eliminates various forms of noise from source MRI and CT images.

- Then, pixel-specific features were retrieved using the DLCNN model, which conducted content-based fusion based on the extracted features. In this instance, the DLCNN is utilised to extract the probability of principal component analysis in each MRI and CT area.

- The post-processing technique is then carried out using a Gaussian filter, which improves the overall texture, spatial, and spectral areas of MRI and CT images.

- The simulation results demonstrate that the suggested approach outperformed standard picture fusion techniques.

The remaining parts of the article are structured as follows: The third portion is dedicated to a comprehensive examination of the literature review. In Section 3, we go through a comprehensive study of the MMIF-Net approach that was suggested. The comprehensive examination of the findings obtained using the suggested MMIF-Net approach is covered in Section 4. The conclusion and analysis of the proposed MMIF-Net approach take up the whole of Section 5.

2. LITERATURE SURVEY

The MS transform [11] is a recognised and potent tool that is extremely useful for fusion applications as well as other applications like segmentation, classification. The following outlines the technique for image fusion that makes use of the MS transform. Initially, MS transform applied on input images to generate the multi domain images. In this transformation, the qualities of an image are formed in a unified space frequency transform [12]. Next, a specific method for fusing various MS representations is applied in order to get a fused output. This approach assumes the activity level of the coefficients, as well as the correlations between surrounding pixels and the coefficients of separate scales, in order to arrive at the result. In order to complete the process, the inverse MS transform is used so that the fused image may be obtained [13]. Having said that, this kind of procedure calls for the resolution of a pair of fundamental difficulties, namely the choice of MSD method and the assumed strategy of fusion that is applied for the fusing of MS representations.

In recent days, a number of different initiatives have been undertaken to fix these two problems. In earlier works [14, 15], fusing images together was accomplished by using MSD approaches such as transforms such as pyramid and wavelet. In more recent works, image fusion was accomplished by using MSD approaches such as a SWT. Initially, LP decomposition [16] and reconstruction are applied in order to combine the images. This technique is used for image fusion that makes use of MATLAB. On the other hand, it is claimed that the LP is unable to accurately depict the images' outlines and contrasts. In order to carry out these tasks, in [17] authors proposed a method based on union LP with a number of features for precisely channelizing the significant characteristics from the source medical images into a single fused output. In the beginning, LP is used to map the source medical image into the form of MS transform severally [18]. After that, an effective strategy of fusion was established in order to unify the pyramid coefficients. In order to complete the process of fusing images, the inverted pyramid reconstruction technique is used at the very end. However, the image fusion metrics that are employed in this only evaluate the quality of the fused image from a limited perspective [19], and it may be extremely challenging to determine which objective measure is significantly more relevant to improve.

After some time had passed, a fresh approach to the merging of multi-modal medical pictures was introduced in [20]. In order to deconstruct the input anatomical medical pictures and functional medical images into their respective MS image representations depending on the number of levels, this approach makes use of local Laplacian filtering, also known as LLF. After that, the local energy maximum approach is extended so that the approximation images may be fused together [21]. The fusion rule for the decomposed residual images is provided by information of interest-based technique. The last step is to do an inverse LLF in order to acquire the output image. On the other hand, LLF is not as quick to run as some of the other MS tools, and the superiority of these approaches need to be validated by the higher metric results. The fusion rule that is used here results in less colour information being introduced [22]. As a result, certain additional MS transforms have been applied in order to improve the performance of the fusion. The DWT is now the most widely used method of MS fusion. As a consequence of its superior ability to non-traditionally represent spatial and spectral information [23], it is capable of producing fusion results that are far superior to those produced by pyramid transforms.

In [25], there is a proposal for a fusion methodology for medical pictures that makes use of a global energy method and is based on sub images that have the same scale, and the DWT is used in order to accomplish this selection. Using DWT in conjunction with the spatial frequency methodology, the authors of [26] suggested an original method for merging PET-MRI data. By using this strategy, the influence of picture imbalance and the occurrence of fusion image blurring are both reduced, which contributes to an overall improvement in the clarity. Using the human visual system (HVS) and multimodal wavelet transform, the authors of [27] presented a multimodal medical picture fusion technique. This method unifies and benefits of both HVS and wavelet transform to achieve superior fusion performance. After the wavelet transform algorithm has been used to breakdown the source images that are going to be fused,

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then HVS algorithm was employed for coefficient selection [28]. Inverse WT is then used in order to complete the process of fusing the medical image.

In [29] authors provided a unique method for the augmentation of MRI and PET images utilising DWT, as well as the fusion of those improved images. In the beginning, the source medical images that have been deteriorated and unreadable as a result of a number of different circumstances are pre-processed. At the same time, the quality of the input images is improved by utilising Gaussian filters [30]. After these images have been improved, the DWT is applied to brain areas that have varying amounts of activity. In comparison to the conventional methods of medical fusion, it demonstrated an accuracy improvement of around 80-90 percent, reduced colour distortion, and no loss of anatomical information. The DWT-based fusion methods, on the other hand, have problems with aliasing, shift variance, and directionality lack problems [31]. In further research, a SWT-based medical image fusion technique was developed to circumvent the shift variance constraint. The rotating WT for medical image fusion was recently published in [32]. This method utilizes a hybrid transform, which recovers more spectral characteristics in various orientations than SWT, DWT. On the other hand, it suffers from a lack of directionality, which is a non-rectifiable problem. Dual-tree complex wavelet transformations (DT-CWT) [33] are used for the purpose of productively fusing images in order to circumvent the aforementioned restrictions. The primary advantages of the DT-CWT over other WT variations such as SWT, DWT are its shift invariance and directional selectivity [34], both of which help to reduce the artefacts that are introduced by these two versions.

3. PROPOSED SYSTEM

In many different computer vision applications, image fusion serves as the primary focus of attention. The standard image processing approaches, on the other hand, were not successful in carrying out the fusion procedure. As a result, the primary emphasis of this study was placed on the creation of a multi-model picture fusion network using a deep learning convolutional neural network. There are 5 major steps involved in the process of mechanisms of image fusion system as illustrated in Figure-1. To begin, a preprocessing operation is performed on the source MRI and CT images using a median filter. This filter gets rid of the various forms of noise that are present in these pictures. After that, pixel-specific features were retrieved with the help of the DLCNN model, which carried out the feature-specific content-based fusion. To extract the probability of principal component analysis in each MRI and CT area, the DLCNN is applied here. After that, the Gaussian filter is used to carry out the post-processing operation, which results in an improvement to the overall texture, as well as the spatial and spectral areas of the MRI and CT images.

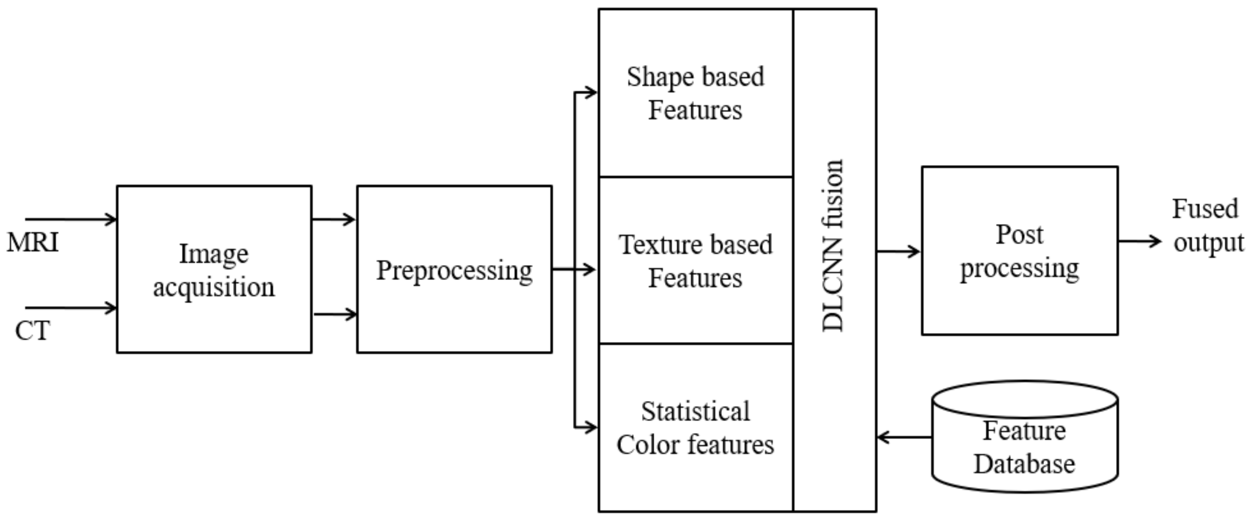

Figure-1. Proposed image fusion network.

3.1 Preprocessing

Illumination refers to the light that comes from a source and falls on an object, while reflectance refers to the amount of light that is reflected from an object after it has been illuminated. Utilizing a sensor array allows for the capture of the visual data present in a portion of a scene as a digital image that is processed using f(x, y). Because every essential component of the sensor array has the same design, the image obtained by using the sensor array is what's known as "single sensor image capture," and it's what's used when the array is used alone. Knowing the specifics of a display that makes use of multiple sensor arrays, each of which operates at a different range of wavelengths, is fascinating for us. This method is referred to as picture capturing using numerous sensors. In the following discussions, it is clarified that a sensor array is replaced by a phase senor in its operational capacity.

When acquiring images of a directed scene using a single sensor, it is possible that not all of the relevant information will be rendered. In some circumstances, a

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couple of images or many images are necessary for improved ocular realising. These pictures accurately depict information that is either complementary or optically discrete. An expert in diagnosis (technician) is not always capable of unifying and commenting on a complex image that is comprised of these captivates of multiple images. The noise or artefacts that were introduced during the process of acquiring the image are reduced or eliminated during this stage of processing. It is the process of aligning multiple images of the same scene in accordance with a coordinate system. It is also known as image registration. During this procedure, certain source images were chosen to serve as the reference image. The other source pictures are then subjected to a geometric modification in order to detach them in accordance with the reference image.

3.2 Image Fusion

The CNN image fusion mostly utilizes multi-focus imaging and multi-exposure imaging. However, this system had some drawbacks. The factors like luminescence and sensors with dynamic range affect the system, for instance, visible image sensor can capture better visual images in high luminescent conditions, but they fail to capture good images at low luminescent conditions. Therefore, DLCNN fusion was put in action to repair the drawback of basic fusion systems while the images are captured in unfavourable conditions. Figure-2 shows the process of DLCNN fusion. The DLCNN is comprised of a process where the same scene is captured by multiple images via sensors of various modalities for the acquisition of interrelated information. Let us take MRI sensors where the equipment works properly in high and intensive lightening conditions. Nevertheless, CT sensors work properly in low and less intensive lightening conditions. The fusion process condenses all of the necessary information from various pictures into a single image. The pixel-level fusion process is carried out, pixel by pixel, on each individual input picture. The fusion procedure that is performed at feature level on the input image features those are educed, while it is executed on probabilistic conclusion info of local conclusion shaper at decision level, which are successively formulated from the features evoked. The approaches based on feature level are more desirable for fusion contrasted to another level method since their efficacious and ease of development. Image fusion is a process of merging comprehensive visual information of various co-registered image of distinct sources into a single image. The result of an fused image provides more precise description of a display than an individual source images.

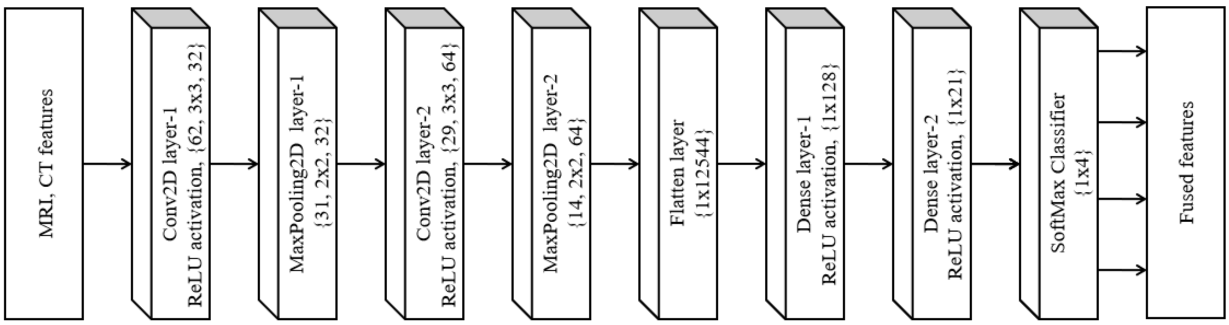

Figure-2. DLCNN fusion.

Advantages of DLCNN fusion systems are:

- **Reliable and precise information:** This type of fusion systems provides an authentic and precise illustration of the scene in contrast to the source images.
- **Agile performance:** The fusion system mechanisms produce a segregated image by considering the superfluous information of all sensors, despite the failure of one sensor. Hence, it is agile.
- **Condensed representation:** The mechanism of this system is condensed which furnishes all the required information of various source images into a singular image.
- **Broad functioning range:** The scale of functioning is expanded by capturing images at distinctive functioning constraints of the sensors.
- **Profound certainty:** Amalgamated data from numerous sensors decreases the unpredictability in the individual snapshots of the scene or display.

3.3 Post-processing

At this phase the developed fused images are further processed based on the application requirement. This processing may involve recognition, segmentation, classification, and feature extraction. The fused images acquired from the above-illustrated images will assist in computer-guided surgeries and radio surgery for enhanced diagnosis and treatment which is an easy task for a radiologist to conduct. The amalgamation of essential visual info in the source images to acquire a precise image is sacrosanct for a better understanding of the scene.

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4. RESULTS AND DISCUSSIONS

In this part, a comprehensive examination of the simulation findings is presented. In addition, the performance of the suggested method is evaluated in comparison to the most recent and cutting-edge techniques. Here, performance metrics like peak signal to noise ratio (PSNR), root mean square error (RMSE), correlation coefficient (CC), structural similarity index metric (SSIM), entropy are considered. The simulations were conducted on BraTS-2020 [35] dataset.

4.1 Subjective Evaluation

Figure-3 fusion performance on images sample set-1 and Figure-4 fusion performance on images sample set-2. Here, the proposed DLCNN resulted in accurate texture-based fusion as compared to conventional RNN [22], PNN [25] fused outcomes. Here, the existing methods are suffering with higher losses.

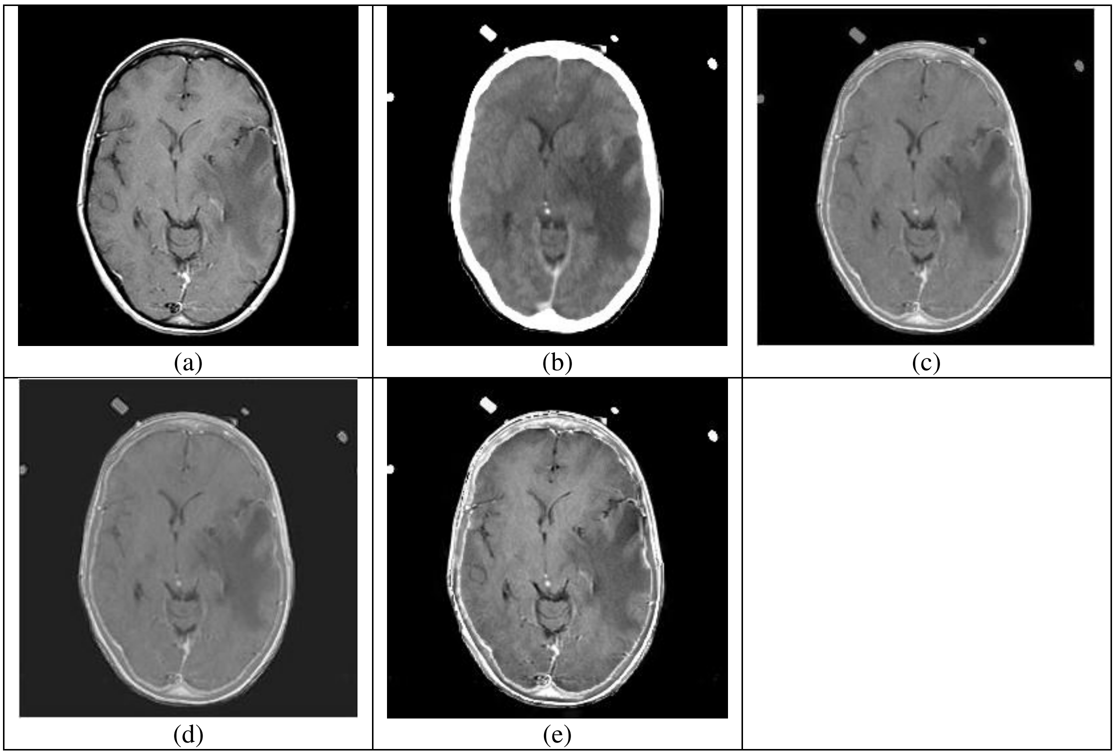

Figure-3. Fusion performance on images sample set-1 (a) MRI, (b) CT, (c) RNN [22] fused outcome, (d) PNN [25] fused outcome, (e) proposed DLCNN fused outcome.

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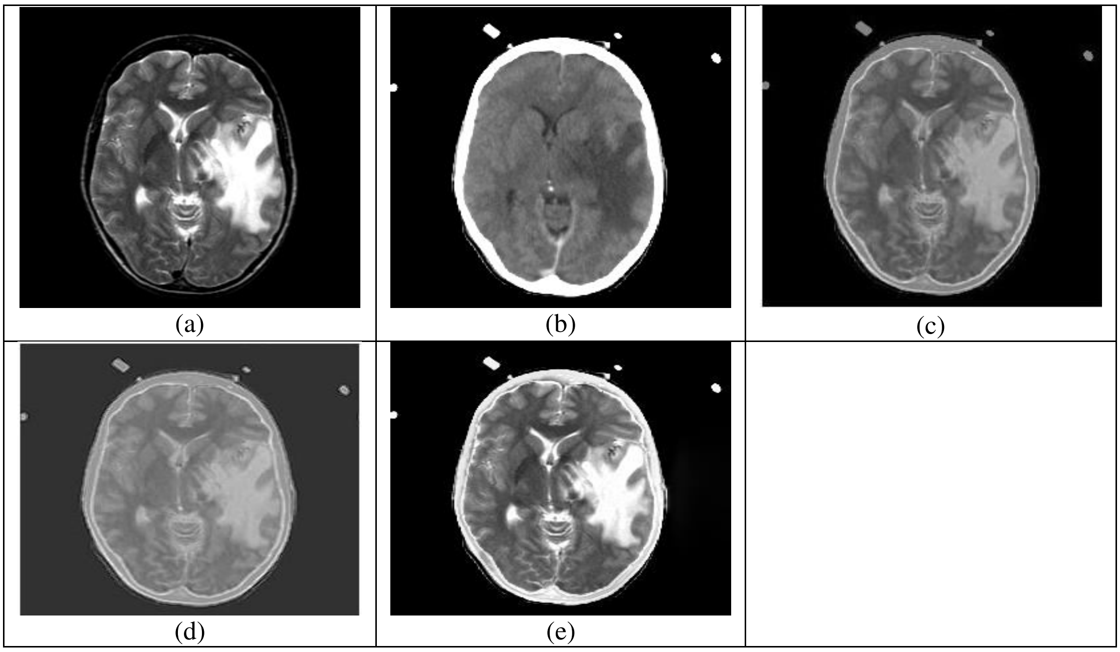

Figure-4. Fusion performance on images sample set-2 (a) MRI, (b) CT, (c) RNN [22] fused outcome, (d) PNN [25] fused outcome, (e) proposed DLCNN fused outcome.

4.2 Performance Analysis

Table-1 compares the performance of various fusion methods. At the time of fusion process, the needed information from the source could be misplaced and redundant info may enter into the fused image. Therefore, the algorithms of fusion are needed to be evaluated for an enhanced performance. The analysis of the performance is carried out by assessing qualitatively by visual scrutiny and fusion metric for quantitative measurement. The performance of proposed method resulted in improved PSNR, SSIM, Entropy, CC, and reduced RMSE as compared to RNN [22], PNN [25], ANN [27], DWT-PNN [29], and DQNN [32] methods.

Table-1. Performance comparison of fusion methods.

Methodology	PSNR (in dB)	RMSE	CC	SSIM	Entropy
RNN [22]	67.394	0.173	0.746	0.8374	0.374
PNN [25]	69.495	0.0827	0.836	0.8734	1.384
ANN [27]	72.349	0.083	0.847	0.973	1.38
DWT-PNN [29]	75.679	0.071	0.937	0.9384	2.193
DQNN [32]	78.384	0.139	0.928	0.9276	3.82
Proposed method	90.51	0.00047	1	1	4.37

5. CONCLUSIONS

In many different computer vision applications, image fusion serves as the primary focus of attention. The standard image processing approaches, on the other hand, were not successful in carrying out the fusion procedure. As a result, the primary emphasis of this study was placed on the creation of a multi-model picture fusion network using DLCNN. To begin, a pre-processing operation is performed on the source MRI and CT images using a median filter. This filter gets rid of the various forms of noise that are present in these pictures. After that, pixel-specific features were retrieved with the help of the DLCNN model, which carried out the feature-specific content-based fusion. To extract the probability of principal component analysis in each MRI and CT area, the DLCNN is applied here. After that, the gaussian filter is used to carry out the post-processing operation, which results in an improvement to the overall texture, as well as the spatial and spectral areas of the MRI and CT images. Based on the findings of the simulations, it is clear that the suggested technique yielded superior results than those obtained using the more traditional picture fusion methods. Further, this work can be extended with the segmentation, classification tasks for identifying the benign and malignant tumours.

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