A
Major Project Report

On

“Enhancing Medical Diagnosis Through Multimodal Medical Image Fusion”

Submitted in partial fulfillment of the

Requirements for the award of the degree of

Bachelor of Technology

In

Computer Science & Engineering –

Artificial Intelligence & Machine Learning

By

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2024

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CERTIFICATE

This is to certify that the project entitled **“Enhancing Medical Diagnosis Through Multimodal Medical Image Fusion”** has been submitted by **Kolli Meghana (20R21A6625), Linga Bhargavi (20R21A6628), C Sai Shreeya (20R21A6611), Veeranki Tiruneswar (20R21A6653)** in partial fulfilment of the requirements for the award of degree of Bachelor of Technology in Computer Science & Engineering – Artificial Intelligence & Machine Learning from Jawaharlal Nehru Technological University, Hyderabad. The results embodied in this project have not been submitted to any other University or Institution for the award of any degree or diploma.

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DECLARATION

We hereby declare that the project entitled **“Enhancing Medical Diagnosis Through Multimodal Medical Image Fusion”** is the work done during the period from **January 2024 to May 2024** and is submitted in partial fulfilment of the requirements for the award of degree of Bachelor of Technology in Computer Science & Engineering – Artificial Intelligence & Machine Learning from Jawaharlal Nehru Technology University, Hyderabad. The results embodied in this project have not been submitted to any other university or Institution for the award of any degree or diploma.

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ABSTRACT

The diagnosis of patients and the effectiveness of treatment are significantly impacted by the timely and accurate detection of brain tumors. This application utilizes wavelet transform techniques to incorporate MRI (Magnetic Resonance Imaging) and CT (Computed Tomography) scan images from multimodal medical imaging. Procrustes analysis guarantees alignment in CT and MRI imaging techniques. The fused images offer a thorough understanding of both neuroanatomy and functionalities. The CNN (Convolutional Neural Network) analyses these combined images to detect and pinpoint tumors. The deep learning model utilizes merged images to enable quicker and more precise detection of tumors. After detecting them, it categorizes tumors as either glioma, meningioma, or pituitary tumor sub-type. Precise identification of tumor sub-types aids in targeted treatment, decreases the chance of adverse reactions, enhances treatment effectiveness, and ultimately betters the quality of life for patients. This Flask-based tool offers a user-friendly interface and convenient access, allowing healthcare providers to easily navigate the diagnostic process and accurately analyse outcomes. This platform streamlines radiology procedures and fosters cooperation between imaging experts, cancer specialists, and brain surgeons, ultimately enhancing the quality of patient treatment.

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LIST OF ABBREVIATIONS

ABBREVIATIONS

MRI	**Magnetic Resonance Imaging**
CT	**Computed Tomography**
CNN	**Convolutional Neural Network**
DWT	**Discrete Wavelet Transforms**
PET	**Post Emission Tomography**

APPENDIX-4

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CHAPTER 1

INTRODUCTION

1.1 OVERVIEW

Brain tumors are abnormal growths of cells within the brain or surrounding tissues. These tumors represent a significant health challenge, with varying degrees of severity and complexity. Timely and accurate analysis is essential in identifying the precise treatment plan and enhancing patient results. Advanced imaging techniques, like CT and MRI, are combined in multimodal clinical imaging to provide a radical expertise of mind tumors. CT scans use X-rays to acquire targeted anatomical facts, showing the vicinity, size, and any structural modifications of the tumor in the brain. On the opposite hand, MRI uses robust magnetic fields and radio waves to produce special images of tender tissue, presenting precious data on tumor features along with kind, grade, and how far it has spread into close by areas of the brain. Through advanced algorithms and techniques, the combination of different imaging modalities can provide a complete view of the brain's shape and tumor traits, assisting in precise diagnosis and customized treatment techniques. Furthermore, following tumor detection, their types are similarly labeled as glioma, a tumor that comes from glial cells inside the brain or spinal cord; meningioma, which originates from the meninges of the brain or spinal cord; and pituitary tumors, observed within the pituitary gland at the base of the brain, offering greater precise insights at the particular pathology for more targeted remedy options.

1.2 PURPOSE OF THE PROJECT

The purpose of the project is to develop innovative solution that combines multimodal medical imaging with artificial intelligence for accurate and rapid diagnosis of brain tumors, improving patient care and outcomes .Its significance lies in overcoming the limitations of traditional methods, with a comprehensive and reliable diagnostic tools that facilitate clinical decision-making, and moreover, have the potential to open new insights into brain tumor pathology, research breakthroughs, and personalized treatment strategies.

1.3 MOTIVATION

The motivation for this project arises from the critical challenges posed through brain tumor diagnosis and its profound effect on patient outcomes. Conventional diagnostic strategies often lack the sensitivity and specificity required, leading to potential misdiagnoses or delays in detection, which could have extreme results. Accurately distinguishing and characterizing tumor types is vital for guiding suitable remedy strategies, yet present methods may fall short in imparting the needful stage of precision. This challenge pursuits to cope with those barriers by using combining the strengths of magnetic resonance imaging (MRI) and computed tomography (CT) imaging modalities with artificial intelligence algorithms. The choice of MRI and CT is pushed by their capability to provide complementary and comprehensive insights into tumor characteristics. The driving force behind this solution is the dedication to improving patient care and outcomes with the aid of addressing the complexities of brain tumor diagnosis through multidisciplinary collaboration and modern technologies. This project seeks to redefine diagnostic requirements in neuro-oncology, enabling personalized and powerful remedy strategies for those devastating conditions, ultimately improving quality of life patients and their families.

CHAPTER 2

LITERATURE SURVEY

An extensive literature survey has been conducted by studying existing systems of Certificate verification and generation. A good number of research papers, journals, and publications have also been referred before formulating this survey.

2.1 EXISTING SYSTEM

Multimodal medical image fusion is a technique that combines images from different imaging modalities like MRI, CT, PET, and SPECT. It involves feature extraction to extract tumor characteristics from each modality, merging these features into a single representation. This aids in tumor localization, characterization, and accurate diagnostic decisions. Different fusion techniques have been developed to address the challenges of tumor identification across multiple imaging modalities which include wavelet, contourlet transform, deep learning-based fusion, multiscale fusion, and pixel, feature, and decision-level fusion methods where each fusion technique leverages the strengths of multiple imaging modalities to provide a more accurate representation of tumors than individual modalities alone.

The responses to various research articles are documented below by the order of the number that have been used to specify them in the references in the end.

1		
Reference in APA format	N. Zsoter et al., "PET-CT based automated lung nodule detection," 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, San Diego, CA, USA, 2012, pp. 4974-4977, Doi: 10.1109/EMBC.2012.6347109.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
PET-CT based automated lung nodule detection | IEEE	Norbert Zsoter, Peter Bandi, Gergely Szardo, Zoltan Toth, Ralph A.	PET-CT, lung nodule detection, segmentation, affinity map, morphological dilation, fuzzy

[Conference Publication | IEEE Xplore]()	Bundschuh, Julia Dinges, Laszlo Papp	connectedness, image analysis, mathematical morphology
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
PET-CT based automated lung nodule detection	Goal: To provide an automated method for detecting lung nodules in PET-CT images and improve accuracy and efficiency of nodule detection. Problem: The time consuming and subjective nature of manual evaluation of PET-CT images for lung nodules which can lead to misdiagnosed nodule.	This paper presents an automated method for detecting lung nodules in PET-CT images, which includes lung affinity map generation, nodule detection, nodule classification, and post-processing, resulting in an accurate and efficient method.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed model provides a single fused image of different modalities like PET, MRI and CT which contains more comprehensive and reliable data for better clinical diagnosis.

	Process Steps	Advantage	Disadvantage (Limitation)

1	Image acquisition and preprocessing of the PET-CT images.	The use of attenuation and SUV correction improves the accuracy of the PET images, while Hounsfield correction improves the accuracy of the CT images.	Preprocessing can be time consuming as requires specialized knowledge.
2	Adaptive fuzzy segmentation generates four fuzzy affinity maps, which are used to detect lung nodules in the PET-CT images.	The automatic detection of the lungs inside of the CT images, which can improve the accuracy of nodule detection.	
3	The initial nodule detection and classification.	The multiple fuzzy-based tissue/organ segmentation enhances nodule detection and prevents merging of nearby nodules.	The need for manual intervention in the nodule detection.
4	The post-processing involves merging nearby nodules and filtering out false positives	Reduces the number of false positives and merging of nearby nodules, which can improve the accuracy of the final results.	The potential for false positives and false negatives, and the need for further validation in larger patient cohorts.

Major Impact Factors in this Work

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Lung nodule detection effectiveness: It is influenced by the use of foreground and	Foreground and background mean ratio: It is used independently for each nodule to detect	Post processing step (Split-up): It moderates the relationship between the mean ratio-based	CT image and Lung segmentation: The CT image is used to classify the detected lesions, and lung

background mean ratio and the subsequent steps in the algorithm.	the region of nodules properly in PET-CT studies.	detection and the final classification step, particularly in cases where nearby and similar nodules are merged into one.	segmentation helps to build the basis for this classification. These variables mediate the relationship between the mean ratio and the nodule detection effectiveness.

Relationship Among the Above 4 Variables in This article
The mean ratio, CT image, and lung segmentation all play a crucial role in lung nodule detection, with a more accurate ratio enhancing detection effectiveness. Post-processing steps also refine detection results.

Input and Output		**Feature of This Solution**	**Contribution & The Value of This Work**
Input	**Output**	The use of multiple fuzzy based tissue/ organ segmentation approaches to automatically detect the lungs inside of CT images, which can help improve the accuracy of the nodule detection.	This work develops an automated method for lung nodule detection in PET-CT images, improving accuracy, efficiency, and reducing physician workload, potentially improving patient outcomes and clinical practice.
PET-CT image of the torso of the body which always fully includes the lungs.	A set of detected lung nodules which are represented as 3D regions of interest (ROIs) in the PET-CT image.		

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**

This work presents an automated method for lung nodule detection in PET-CT images, which can improve accuracy, reduce physician workload, and be integrated into existing clinical workflows as it could lead to earlier detection of lung cancer and other diseases.	The method may not be effective for detecting very small nodules or nodules that are located in difficult-to-reach areas of the lung, which could limit its utility in some cases.

Analyse This Work by Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
This study presents an automated method for detecting lung nodules in PET-CT images, improving accuracy and efficiency. Validated on real clinical cases, it has potential for clinical practice. However, limitations include initial lung segmentation accuracy and potential for small or difficult-to-reach nodules.	Interview Fusion clinical evaluation software and various mathematical and image analysis methods such as fuzzy connectedness, morphological dilation, and multiple fuzzy-based tissue/organ segmentation approaches.	Abstract I. Introduction II. Materials and methods III. Results IV. Conclusion and future works

Diagram/Flowchart

---End of Paper 1---

2	
Reference in APA format	C. Hima Bindu and K. Veera Swamy, "Medical image fusion using content based automatic segmentation," International Conference on Recent Advances and Innovations in Engineering (ICRAIE-2014), Jaipur, India, 2014, pp. 1-5, doi: 10.1109/ICRAIE.2014.6909206.

URL of the Reference	Authors Names and Emails	Keywords in this Reference
https://ieeexplore.ieee.org/document/6909206	Ch. Hima Bindu, K. Veera Swamy	Image segmentation, Biomedical imaging, PSNR, Computers, Magnetic resonance imaging
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
Medical Image Fusion using Content Based Automatic Segmentation	The goal of this solution is to achieve less complex fusion and improve the performance of image fusion methods compared to existing methods. The problem that needs to be solved is the limitations of pixel level image fusion methods such as sensitivity to noise, blurring effects, and miss registration.	The proposed solution consists of a multi-modal convolutional neural network approach for medical image segmentation, which includes three schemes for fusing information from different image modalities: fusing at feature level, fusing at classifier level, and fusing at decision level.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed MS-DAYOLO framework improves the robustness and accuracy of object detection in cross-domain scenarios, making it a promising solution for real-world applications.

	Process Steps	Advantage	Disadvantage (Limitation)

1	Conceptual design for image fusion schemes, including fusing at feature level, fusing at classifier level, and fusing at decision level.	it provides a unified framework for multi-modal image processing, which can guide the methodology design for various applications.	it may not be suitable for all scenarios, and some modifications may be necessary.
2	Preprocessing of the multi-modal soft tissue sarcoma imaging dataset.	it can improve the quality of the input data and reduce noise and artifacts.	it may introduce bias or errors if not done carefully.
3	Training and testing of the three image segmentation models based on the Convolutional Neural Network (CNN) structure.	it can optimize the model parameters and improve the accuracy and robustness of the segmentation.	it requires a large amount of labeled data and computational resources.
4	Evaluation of the performance difference across different fusion schemes and the cause thereof.	it can provide insights into the performance difference across different fusion schemes and the cause thereof.	it may not be able to capture all aspects of the problem and may require further investigation.

Major Impact Factors in this Work

This work's major impact factors include the use of multi-modal image fusion, a novel conceptual image fusion architecture, the use of Convolutional Neural Networks (CNNs), and the evaluation of performance differences across different fusion schemes, contributing to improved medical image segmentation.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable in this study is the accuracy of medical image	The independent variable in this paper is the type of multi-modal image fusion	it does use cross-validation and multiple evaluation metrics to control for	The study focuses on optimizing the multi-modal image fusion architecture for

segmentation, measured by the Dice similarity coefficient (DSC) and the Hausdorff distance (HD), which reflect the overlap and distance between predicted and ground truth segmentation masks, respectively.	scheme used for medical image segmentation, which includes three different fusion architectures: early fusion, late fusion, and hybrid fusion. These architectures combine the information from MRI, CT, and PET images at different stages of the deep learning pipeline to optimize the accuracy and robustness of the segmentation algorithm.	potential confounding factors and provide a comprehensive assessment of the segmentation accuracy.	medical image segmentation, rather than examining the underlying mechanisms or processes that may mediate the relationship between the input images and the segmentation output.

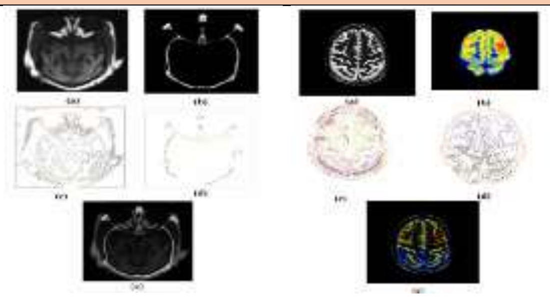
Relationship Among The Above 4 Variables in This article
the relationship among mediating (intervening) variables, moderating variables, dependent variables, and independent variables. The study focuses on optimizing the multi-modal image fusion architecture for medical image segmentation, with the segmentation accuracy as the dependent variable and the multi-modal image fusion architecture as the independent variable. The study does not examine the underlying mechanisms or processes that may mediate or moderate the relationship between the input images and the segmentation output.

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**

<table>
<tr>
<td><table><tr><th>Input</th><th>Output</th></tr><tr><td>The input of this paper is the use of deep learning to optimize the multi-modal image fusion architecture for medical image segmentation for MRI, CT, and PET images.</td><td>The output is a generalized framework of image fusion for supervised learning in biomedical image</td></tr></table></td>
<td>solution features the use of multi-modal image fusion, a novel conceptual image fusion architecture, the use of Convolutional Neural Networks (CNNs), and the evaluation of performance differences across different fusion schemes. These features contribute to improved accuracy and robustness of medical image segmentation.</td>
<td>Our work contributes a novel multi-modal image fusion architecture for medical image segmentation using Convolutional Neural Networks (CNNs), which has the potential to improve the accuracy and robustness of medical image segmentation. This work advances the state-of-the-art in medical image analysis by providing a comprehensive evaluation of different fusion schemes and their impact on segmentation performance, and by providing insights into the characteristics of the feature learning and impact of errors on the learning process.</td>
</tr>
</table>

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The proposed multi-modal image fusion architecture for medical image segmentation has the potential to improve the accuracy and efficiency of soft tissue sarcoma detection, which can ultimately lead to better patient outcomes.	The feature-level fusion scheme in the proposed image segmentation system based on deep Convolutional Neural Network (CNN) can suffer from decreased robustness due to the presence of large errors in one or more image modalities.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The analysis reveals noteworthy aspects of the	CT -MRl and MRl-PET	I. Introduction II. Image Fusion

work. The study presents an innovative approach to multi-modal medical image segmentation, but its limited scope and lack of comprehensive comparative analysis may restrict the generalizability of the proposed image fusion schemes.		III. Proposed Method IV. Experimental Results V. Conclusion
Diagram/Flowchart		
		

---End of Paper 2---

3

Reference in APA format	Himanshi, V. Bhateja, A. Krishn and A. Sahu, "An improved medical image fusion approach using PCA and complex wavelets," 2014 International Conference on Medical Imaging, m-Health and Emerging Communication Systems (MedCom), Greater Noida, India, 2014, pp. 442-447, doi: 10.1109/MedCom.2014.7006049.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/7006049	Himanshi, Vikrant Bhateja, Abhinav Krishn and Akanksha Sahu	CT-Scan, DTCWT, Entropy, MRI and PCA.

The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	The Goal (Objective) of this Solution & What is the problem that need to be solved	What are the components of it?
Improved medical image fusion approach using PCA and Complex Wavelets.	Goal is to combine MR and CT-scan images to create a single image that contains more information than either of the original images. Problem is to solve the limited information available in individual medical images for the doctors to make accurate diagnosis.	Gray scale conversion, DTCWT decomposition, PCA and image fusion.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The process includes converting MRI and CT-scan images to grayscale, decomposing with DTCWT, using PCA for resolution improvement, and fusing to create an information-rich single image.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Conversion the MRI and CT-scan images from RGB scale to Gray scale to ensure that the images have the same color space and can be processed together.	Simplifies the image processing by reducing the dimensionality of the images.	May result in some loss of information, particularly if the original images contain important color information

2	Decomposing the source images using Dual Tree Complex Wavelet Transform (DTCWT) into frequency bands, including a lower-frequency band and other higher-frequency bands.	DTCWT provides shift invariance and improved directionality along with preservation of spectral content.	DTCWT is computationally intensive and may require more processing power than other wavelet transforms.
3	The decomposed images are then processed using Principal Component Analysis (PCA) based fusion rule to improve upon the resolution and reduce redundancy.	PCA can reduce the dimensionality of the images and remove redundant information, resulting in a more efficient and effective fusion process.	PCA may result in some loss of information, particularly if the original images contain important features that are not captured by the PCA.
4	Fusing the processed images to create a single fused image that contains more information than either of the original images.	The fused image provides a more complete picture of the patient's condition, which can help doctors make more accurate diagnoses.	The fusion process may result in some loss of information, particularly if the original images contain important features that are not captured by the fusion process.

Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
The dependent variable in this work is the visual quality and fusion metrics of the fused medical	The combination of Principal Component Analysis (PCA) and Dual Tree Complex Wavelet (DTCWT)	Factors influencing the performance of the proposed fusion approach in comparison to other	The shift invariance and high directionality property of DTCWT, along with the feature

image obtained through the proposed PCA and Dual Tree Complex Wavelet (DTCWT) fusion approach.	constitutes the independent variable.	methods serve as moderating variables.	enhancement property of PCA, act as mediating variables.

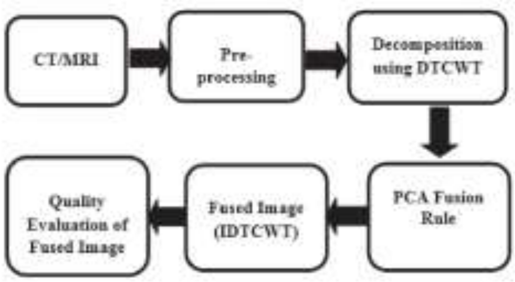
Relationship Among The Above 4 Variables in This article
The PCA and DTCWT fusion approach, as the independent variable, is anticipated to impact the visual quality and fusion metrics of the fused medical image (dependent variable), with the comparison to other approaches moderating this relationship. The success of the fusion process depends on mediating variables like shift invariance, directionality, and feature enhancement properties.

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**
<table><tr><th>Input</th><th>Output</th></tr><tr><td>MR and CT- scan images</td><td>A fused image</td></tr></table>	The use of DTCWT and PCA helps to improve the visual quality of the fused image and increase the effectiveness of the fusion process.	Contribution and the value of this work lies in the proposed improved fusion approach for medical images using PCA and DTCWT. The approach demonstrates an improvement in visual quality of the fused image supported by higher values of fusion metrics.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed approach enhances visual quality, increases fusion process effectiveness with DTCWT and PCA, and improves efficiency through PCA-based fusion rules, contributing to more accurate medical diagnoses.	Challenges such as the computational intensity of DTCWT, potentially increasing processing time and cost, and the risk of information loss during fusion, impacting diagnosis accuracy.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
This approach combines DTCWT and PCA, showing promise for enhanced visual quality and effectiveness in medical image fusion. However, computational complexity and possible information loss are limitations, requiring further research for validation and addressing these challenges.	Entropy (E) and Fusion Factor (FF) are used as fusion metrics.	Abstract I. Introduction II. Proposed Fusion Approach III. Experimental Results and Discussions IV. Conclusion

Diagram/Flowchart



--End of Paper 3—

4		
Reference in APA format	Z. Guo, X. Li, H. Huang, N. Guo and Q. Li, "Medical image segmentation based on multi-modal convolutional neural network: Study on image fusion schemes," 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), Washington, DC, USA, 2018, pp. 903-907, doi: 10.1109/ISBI.2018.8363717.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**

https://ieeexplore.ieee.org/document/8363717	Zhe Guo, Xiang Li	medical image segmentation, biomedical imaging, medical applications, lesion segmentation, multimodality images
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
Medical image segmentation based on multi-modal convolutional neural network: study on image fusion schemes	This solution aims to propose a generalized framework of image fusion for supervised learning in biomedical image analysis and implement the fusion schemes based on deep convolutional neural network to improve the accuracy and robustness of medical image segmentation using multi-modal convolutional neural networks. The problem that needs to be solved is improving the accuracy and robustness of medical image segmentation.	The proposed solution consists of a multi-modal convolutional neural network approach for medical image segmentation, which includes three schemes for fusing information from different image modalities: fusing at feature level, fusing at classifier level, and fusing at decision level.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

The proposed MS-DAYOLO framework improves the robustness and accuracy of object detection in cross-domain scenarios, making it a promising solution for real-world applications.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Conceptual design for image fusion schemes, including fusing at feature level, fusing at classifier level, and fusing at decision level.	it provides a unified framework for multi-modal image processing, which can guide the methodology design for various applications.	it may not be suitable for all scenarios, and some modifications may be necessary.
2	Preprocessing of the multi-modal soft tissue sarcoma imaging dataset.	it can improve the quality of the input data and reduce noise and artifacts.	it may introduce bias or errors if not done carefully.
3	Training and testing of the three image segmentation models based on the Convolutional Neural Network (CNN) structure.	it can optimize the model parameters and improve the accuracy and robustness of the segmentation.	it requires a large amount of labeled data and computational resources.
4	Evaluation of the performance difference across different fusion schemes and the cause.	it can provide insights into the performance difference across different fusion schemes and the cause thereof.	it may not be able to capture all aspects of the problem and may require further investigation.

Major Impact Factors in this Work

This work's major impact factors include the use of multi-modal image fusion, a novel conceptual image fusion architecture, the use of Convolutional Neural Networks (CNNs), and the evaluation of performance differences across different fusion schemes, contributing to improved medical image segmentation.

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
The dependent variable in this study is the accuracy of medical image segmentation, measured by the Dice similarity coefficient (DSC) and the Hausdorff distance (HD), which reflect the overlap and distance between predicted and ground truth segmentation masks, respectively.	The independent variable in this paper is the type of multi-modal image fusion scheme used for medical image segmentation, which includes three different fusion architectures: early fusion, late fusion, and hybrid fusion. These architectures combine the information from MRI, CT, and PET images at different stages of the deep learning pipeline to optimize the accuracy and robustness of the segmentation algorithm.	it does use cross-validation and multiple evaluation metrics to control for potential confounding factors and provide a comprehensive assessment of the segmentation accuracy.	The study focuses on optimizing the multi-modal image fusion architecture for medical image segmentation, rather than examining the underlying mechanisms or processes that may mediate the relationship between the input images and the segmentation output.

Relationship Among the Above 4 Variables in This article

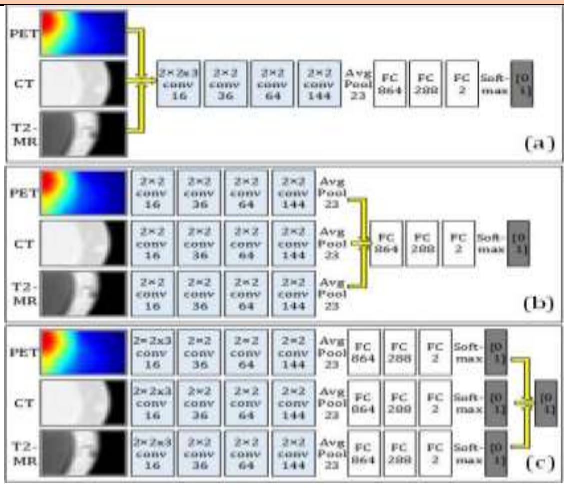
the relationship among mediating (intervening) variables, moderating variables, dependent variables, and independent variables. The study focuses on optimizing the multi-modal image fusion architecture for medical image segmentation, with the segmentation accuracy as the dependent variable and the multi-modal image fusion architecture as the independent variable. The study does not examine the underlying mechanisms or processes that may mediate or moderate the relationship between the input images and the segmentation output.

<table>
<tr><th>Input and Output</th><th>Feature of This Solution</th><th>Contribution & The Value of This Work</th></tr>
<tr><td><table><tr><th>Input</th><th>Output</th></tr><tr><td>The input of this paper is the use of deep learning to optimize the multi-modal image fusion architecture for medical image segmentatio n for MRI, CT, and PET images.</td><td>The output is a generalized framework of image fusion for supervised learning in biomedical image</td></tr></table></td><td>solution features the use of multi-modal image fusion, a novel conceptual image fusion architecture, the use of Convolutional Neural Networks (CNNs), and the evaluation of performance differences across different fusion schemes. These features contribute to improved accuracy and robustness of medical image segmentation.</td><td>Our work contributes a novel multi-modal image fusion architecture for medical image segmentation using Convolutional Neural Networks (CNNs), which has the potential to improve the accuracy and robustness of medical image segmentation. This work advances the state-of-the-art in medical image analysis by providing a comprehensive evaluation of different fusion schemes and their impact on segmentation performance, and by providing insights into the characteristics of the feature learning and impact of errors on the learning process.</td></tr>
</table>

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The proposed multi-modal image fusion architecture for medical image	The feature-level fusion scheme in the proposed image segmentation system based on deep

segmentation has the potential to improve the accuracy and efficiency of soft tissue sarcoma detection, which can ultimately lead to better patient outcomes.	Convolutional Neural Network (CNN) can suffer from decreased robustness due to the presence of large errors in one or more image modalities.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
The analysis reveals noteworthy aspects of the work. The study presents an innovative approach to multi-modal medical image segmentation, but its limited scope and lack of comprehensive comparative analysis may restrict the generalizability of the proposed image fusion schemes.	TensorFlow, Open CV, Dataset, Matplotlib	I. abstract II. Introduction III. Related Work IV. Experiments V. Conclusion

Diagram/Flowchart


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5

Reference in APA format	M. B. Abdulkareem, "Design and Development of Multimodal Medical Image Fusion using Discrete Wavelet Transform," 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), Coimbatore, India, 2018, pp. 1629-1633, doi: 10.1109/ICICCT.2018.8472997.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/8472997	Mohammed Basil Abdulkareem	Resonance Imaging (MRI), Positron Emission Tomography (PET), Multi-modal, medical, discrete wavelet transform (DWT), fusion and Alzheimer's
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
A multi-modal medical image fusion method based on Discrete Wavelet Transform (MST).	Goal is to enhance the quality of medical images for clinical diagnosis through image fusion techniques. Problem is to address the need for precise information in the diagnosis and treatment of disorders, utilizing various modalities of medical image.	1. Preprocessing of input images 2. Decomposition of input images using Discrete Wavelet Transform (DWT) 3. Fusion of decomposed images using a fusion rule 4. Inverse Discrete Wavelet Transform (IDWT) to obtain the fused image 5. Post-processing of the fused image

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process
The proposed image processing workflow involves preprocessing with Gaussian filters, decomposition using Discrete Wavelet Transform (DWT) for multi-resolution representation, fusion through a weighted average method, obtaining the fused image via Inverse DWT (IDWT), and post-processing with a color dilation method.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Gaussian filters of spatial filtering techniques are applied for preprocessing to enhance the quality of the input images which are degraded and non- readable.	Improves the quality of the input images, making them more suitable for further processing	It may introduce some blurring in the images.
2	The enhanced images are decomposed using DWT, which is a mathematical technique for signal processing.	Provides a multi-resolution representation of the input images, which can capture both the fine and coarse details of the images.	It may introduce some artifacts in the decomposed images.
3	Decomposed images are fused using a weighted average fusion rule, combining information from different modalities of medical images.	Provides a more accurate and comprehensive diagnosis by combining the information from different modalities.	The choice of fusion rule may affect the quality of the fused image.
4	The fused image is obtained by applying IDWT to the fused decomposed images.	Provides a high-quality fused image that preserves both the spectral and anatomical data	It may introduce some artifacts in the fused image.

5	The fused image undergoes post-processing to further enhance quality through a color dilation method	The quality of the fused image is improved	it may introduce some color distortion in the fused image.

Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The quality of the fused medical images, particularly in terms of enhanced anatomical and spectral information, serves as the dependent variable.	The application of Gaussian filters for spatial filtering in the pre-processing stage and the use of DWT for fusing different brain regions constitute the independent variables.	Color Dilution in the fusion process plays a moderating role in achieving accurate outcomes.	The use of pre-processing techniques, including Gaussian filters and DWT, acts as an intervening variable influencing the quality of the enhanced images

Relationship Among The Above 4 Variables in This article

The application of pre-processing techniques (independent variable) influences the quality of enhanced images (mediating variable), which, in turn, affects the quality of the fused medical images (dependent variable). The moderating variable, color dilution, also plays a role in achieving accurate outcomes.

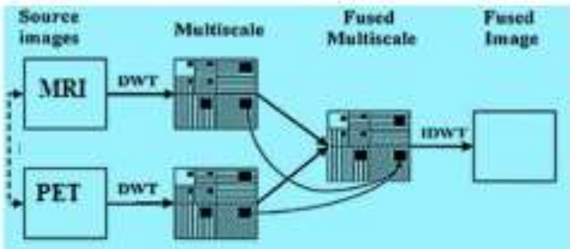
Input and Output		Feature of This Solution	Contribution in This Work
Input	**Output**	Utilizes Discrete Wavelet Transform (DWT) for image decomposition, employs a fusion rule for combining information from diverse modalities, and incorporates post-processing techniques to	Contribution lies in the experimental results of the proposed method using DWT has demonstrated that the proposed method outperforms other existing techniques in terms of image quality and
PET and MRI images of brain	A fused image		

	enhance the fused image quality.	preservation of important features.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
It achieves high accuracy outcomes and preserves both the spectral and anatomical data, making it a valuable tool for medical image processing.	It may introduce some artifacts and distortions in the processed images.

Analyse This Work by Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
The proposed solution, using Discrete Wavelet Transform (DWT), significantly enhances medical image quality for clinical diagnosis, achieving 90-95% more accuracy. Tested on Alzheimer's and normal brain image datasets, DWT improves fused image quality, with effectiveness depending on specific datasets and performance measures.	Root mean square error (RMSE), percentage fit error (PFE), signal to noise ratio (SNR), peak signal to interference ratio (PSNR), correlation coefficient (CC), mutual information (MI), universal quality index (UQI), structural similarity index measure (SSIM)	Abstract I. Introduction II. Related Work III. Proposed Fusion Approach IV. Experimental Analysis V. Conclusion

Diagram/Flowchart



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6		
Reference in APA format	K. Vanitha, D. Satyanarayana and M. N. G. Prasad, "Multimodal Medical Image Fusion Based on Hybrid L1- L0 Layer Decomposition Method," 2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Kanpur, India, 2019, pp. 1-5, doi: 10.1109/ICCCNT45670.2019.8944896.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/8944896	K.Vanitha, Dr.D.Satyanarayana and Dr.M.N.Giri Prasad	Multimodal medical image fusion, hybrid l1-l0 decomposition, base layer, detail layer.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Multimodal medical image fusion that combines multiscale decomposition and hybrid l1-l0 decomposition	The goal of this work is to develop a new method for multimodal medical image fusion that can provide a more complete and accurate representation of the underlying anatomy or pathology. Problem: Medical images often have poor contrast and may not provide enough information for	1. Hybrid l1-l0 decomposition model 2. Weighted average fusion rule 3. Average fusion rule 4. Linear combination 5. Objective criteria

	accurate diagnosis or treatment planning.	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed method uses a hybrid l1-l0 decomposition model and weighted average fusion rule to combine detailed information, average fusion rule for base layers, and a linear combination for the final fused image, evaluated with objective criteria for performance comparison.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Hybrid l1-l0 decomposition model is used to decompose the source images into base and detail layers, which contain information about edges, boundaries, and contours.	It can preserve edges and contours while reducing noise and artifacts in the image.	It may not be suitable for all types of images and may require careful tuning of parameters.
2	Weighted average fusion rule is used to identify the detailed information in the source images and combine it into a single fused image	It can preserve fine details and textures in the image, which may be important for accurate diagnosis or treatment planning	It may also introduce artifacts or noise if the weights are not carefully chosen.
3	Average fusion rule is used to combine the base layers of the source images into a single fused image.	It can highlight edges, boundaries, and contours in the image, which may be important for visual interpretation.	It may also smooth out or blur important details in the image.
4	The final fused image is obtained by combining the detail and base layers using a linear combination.	It can balance the contributions of the detail and base layers to obtain a	it may also introduce artifacts or noise if the weights are not carefully chosen.

		fused image that is both detailed and informative.	
5	The proposed method is evaluated using objective criteria such as mean, standard deviation, and mutual information to compare its performance with existing methods.	It provides a quantitative measure of the quality of the fused image, which can be used to compare different methods.	It may not capture all aspects of image quality that are important for clinical applications.

Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
The effectiveness and performance of the proposed two-scale decomposition based multimodal medical image fusion method, as measured by objective criteria serve as the dependent variable.	The components of the method, including the hybrid L1-L0 decomposition model, the weighted average fusion rule for detailed information, and the average fusion rule for base layers, constitute the independent variable.	Factors that moderate the relationship between the independent variable and the dependent variable include the reduction of information loss and fusion artifacts.	The transfer of the most important information from the source to the fused image acts as a mediating variable.

Relationship Among the Above 4 Variables in This article
The proposed method's performance (dependent variable) is influenced by the hybrid L1-L0 decomposition model and fusion rules (independent variable), with information loss reduction and fusion artifacts moderation (moderating variable). The transfer of important information

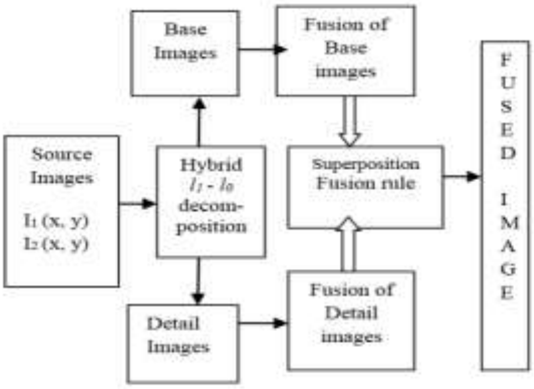
(mediating variable) is crucial, highlighting the overall efficiency and simplicity of the method.

Input and Output	Feature of This Solution	Contribution & The Value of This Work
<table><tr><th>Input</th><th>Output</th></tr><tr><td>CT and MRI images of brain</td><td>A fused image</td></tr></table>	The main feature of this solution is the use of hybrid l1-l0 decomposition model to decompose the source images into base and detail layers, which contain information about edges, boundaries, and contours. The detail layers are then combined using a weighted average fusion rule, while the base layers are combined using an average fusion rule. The final fused image is obtained by combining the detail and base layers using a linear combination.	The contribution of this work is the development of a novel method for multimodal medical image fusion that combines several techniques to obtain a more complete and accurate representation of the underlying anatomy or pathology. Additionally, the objective evaluation criteria used in this work can help researchers compare and benchmark different methods for medical image fusion, which can lead to further improvements in the field.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The proposed multimodal medical image fusion method improves image quality, reduces noise and artifacts using a hybrid l1-l0 decomposition model, and employs objective criteria for quantitative evaluation in the medical imaging.	Potential negative impacts of the proposed solution include complexity due to multiple steps and parameters requiring careful tuning, sensitivity to image characteristics, such as modality and resolution, and a potentially high computational cost for large or high-resolution images, impacting practicality in certain settings.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The proposed method represents a promising approach to multimodal medical image fusion that combines several techniques to obtain a more complete and accurate representation of the image	The performance of the method is evaluated using objective criteria such as mean, standard deviation.	Abstract I. Introduction II. Related Works III. Proposed Method IV. Experimental Results V. Conclusion

Diagram/Flowchart



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7	
Reference in APA format	Jiaxin Li, Houjin Chen, Yanfeng Li, and Yahui Peng. 2019. A Novel Network Based on Densely Connected Fully Convolutional Networks for Segmentation of Lung Tumors on Multi-Modal MR Images. In Proceedings of the 2019 International Conference on Artificial Intelligence and Advanced Manufacturing (AIAM 2019). Association for Computing Machinery, New York, NY, USA, Article 69, 1–5. https://doi.org/10.1145/3358331.3358400

URL of the Reference	Authors Names and Emails	Keywords in this Reference

https://dl.acm.org/doi/abs/10.1145/3358331.3358400	Jiaxin Li, Houjin Chen, Yanfeng Li and Yahui Peng	MR Image segmentation; lung tumour segmentation; multi-modal fusion; fully convolutional networks; Hyper-DenseNet
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
A Novel Network Based on Densely Connected Fully Convolutional Networks for Segmentation of Lung Tumors on Multi-Modal MR Images	The goal is to improve the accuracy of lung tumor segmentation on multi-modal MR images, which is important for the benign and malignant classification of tumors and the choice of subsequent therapy plans. The problem that needs to be solved is the difficulty in accurately segmenting lung tumors due to the complex and diverse appearance of tumors on different modalities.	A densely connected fully convolutional network and a hyper-densely connected CNN model for multi-modality fusion
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		
The proposed solution in this paper uses a deep learning approach to accurately segment lung tumors on multi-modal MR images achieving a high performance.		

	Process Steps	Advantage	Disadvantage (Limitation)
1	The preprocessing of data by selecting slices at the same location for both modalities and resizing the images to a consistent resolution.	Ensures data consistency for deep learning model training.	Potential loss of information if important slices are excluded during resizing.
2	A novel network architecture is used which combines a densely connected fully convolutional network and a hyper-densely connected CNN model for multi-modality fusion.	The novel architecture accurately segments lung tumors, achieving state-of-the-art performance.	Complexity and interpretability challenges; significant computational resources may be required.
3	The network is trained using a combination of binary cross-entropy loss and Dice loss.	Binary cross-entropy and Dice loss combination aids in effective training.	Potential difficulty in tuning hyperparameters, especially balancing between the two loss functions.
4	Dice Similarity Coefficient (DSC) to quantitatively evaluate the performance of the network.	DSC is a widely used metric, providing a quantitative measure of segmentation accuracy.	Limited in capturing all aspects of segmentation performance; comparability across datasets may be challenging.

Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**

Segmentation accuracy of lung tumors from multi-modal MR images, measured by the Dice Similarity Coefficient (DSC).	Multi-Modal fusion strategy and Hyper-DenseNet and U-Net architectures acts as independent variables	The comparison serves as a moderating variable, influencing the evaluation of the proposed method's effectiveness in overcoming deficiencies observed in single-modal images.	The effectiveness of the proposed method is mediated by how well the multi-modal fusion strategy and the combination of Hyper-DenseNet and U-Net architectures contribute to improving segmentation results.

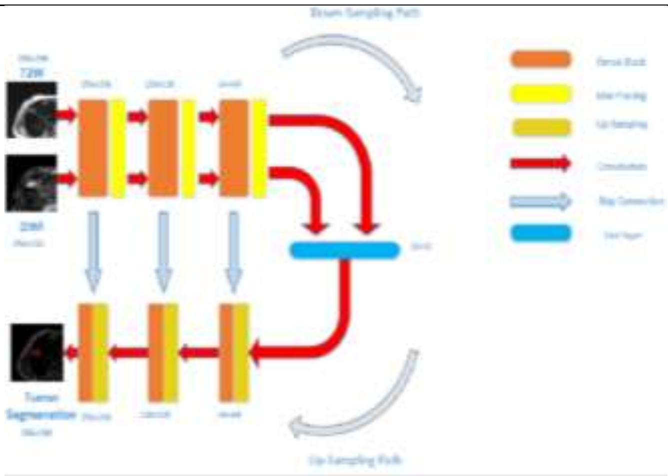
Relationship Among the Above 4 Variables in This article
The independent variables that include multi-modal fusion and network architectures impact lung tumor segmentation accuracy, assessed through comparison to single-modal methods. The effectiveness of the fusion and architecture combination is crucial, emphasizing the proposed method's design in achieving accurate segmentation from multi-modal MR images.

Input and Output		**Feature of This Solution**	**Contribution & The Value of This Work**
Input	**Output**		
MR images of lung tumors, specifically T2-weighted imaging (T2W) and diffusion-weighted imaging (DWI)	Binary segmentation mask that identifies the tumor region in the images.	Key features include combining MR imaging modalities for anatomical and functional information, utilizing a novel network architecture blending U-Net and densely connected CNN characteristics, and assessing performance with Dice Similarity Coefficient (DSC).	The method achieves higher accuracy and better performance in terms of DSC score, sensitivity, and specificity. The value of this work lies in its potential to improve the accuracy and efficiency of lung tumor segmentation, which is a critical step in the diagnosis and treatment of lung cancer.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The method enhances accuracy and efficiency in lung tumor segmentation, a crucial step in lung cancer diagnosis and treatment, with potential applicability to other medical image analysis tasks, improving treatment planning and patient outcomes.	The method's practical application might be hindered in certain settings due to its potential for increased computational demands and longer processing times

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The proposed method combines fully convolutional and hyper-densely connected CNN models for automated lung tumor segmentation on MR images. However, limitations include the need for more computational resources, longer processing time, and etc. Overall, it contributes significantly to medical image analysis and enhancing lung tumor segmentation's accuracy and efficiency.	Use of Dice Similarity Coefficient (DSC) as a quantitative evaluation metric to measure the performance of the proposed network.	Abstract I. Introduction II. Methodology III. Experiments IV. Conclusions

Diagram/Flowchart



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8		
Reference in APA format	K. S. Asish Reddy, K. Kalyan Kumar, K. N. Kumar, V. Bhavana and H. K. Krishnappa, "Multimodal Medical Image Fusion Enhancement Technique for Clinical Diagnosis," 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2019, pp. 586-589, Doi: 10.1109/ICCMC.2019.8819840.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
Multimodal Medical Image Fusion Enhancement Technique for Clinical Diagnosis | IEEE Conference Publication | IEEE Xplore	K Sai Asish Reddy, K Kalyan Kumar, K Naveen Kumar, Bhavana V, Krishnappa H. K	Discrete Wavelet Transform (DWT), Image Fusion, Principal Component Analysis (PCA)
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**

Model/ Tool/ Framework/ ... etc)		
Multimodal Medical Image Fusion Enhancement Technique for Clinical Diagnosis.	Goal: To enhance the accuracy of clinical diagnosis through the fusion of multimodal medical images. Problem: The accurate detection and diagnosis of severe disease cases such as cancer and brain tumor.	The components of the proposed solution include the use of Discrete wavelet transform (DWT), Principal Component Analysis (PCA) for image fusion.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed model provides a single fused image of different modalities like PET, MRI and CT which contains more comprehensive and reliable data for better clinical diagnosis.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Collection of multiple medical images from different modalities, such as PET, MRI, and CT.	Different modalities provide more comprehensive view as they capture different aspects of the medical conditions.	Collecting multiple images can be time consuming and expensive as they may contain different resolution and image quality which can affect the accuracy of fusion process.
2	Preprocessing of input images to remove noise and artifacts.	Preprocessing can improve quality of images and reduce the amount of data required for diagnosis.	Preprocessing can be time consuming and require specialized knowledge as it can remove important details from the images.

3	Applying DWT and PCA algorithms to extract fine details from the images.	These algorithms can extract fine details from the images and are widely used in medical image processing.	These algorithms can be complex and the accuracy of these algorithms can be affected by the quality of the images.
4	Fusing the extracted details into single image using fusion rule.	Fusion can combine the strengths of different modalities and algorithms to reduce the amount of data required for diagnosis.	The choice of fusion rule can affect the accuracy of diagnosis as it introduces artifacts and distortions into the image.
5	Post processing of the fused image to enhance its quality and remove artifacts.	Post processing can improve quality of the final image as it removes the artifacts which can reduce the risk of misdiagnosis.	Post preprocessing can be time consuming and require specialized knowledge as it can remove important details from the final image.

Major Impact Factors in this Work

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Information Content in final fused image: It represents the outcome of the image fusion process and is influenced by the choice of fusion method (DWT and PCA).	DWT and PCA image fusion: This method combines information from multiple images into a single enhanced image.	Performance Parameters: Performance parameters, such as entropy, mean, and standard deviation, serve as moderating variables which moderate the relationship between dependent and	Source input image information: The fusion process aims to preserve and enhance this information during DWT and PCA fusion, ensuring the final image is more informative.

		independent variables.	

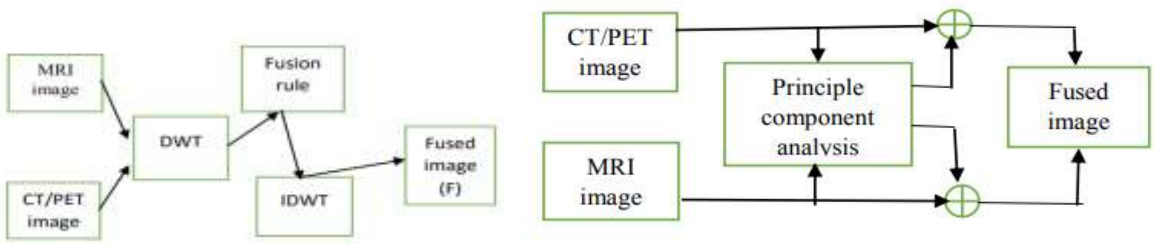
Relationship Among the Above 4 Variables in This article
The choice of DWT and PCA image fusion directly influences the final fused image's information content, with the source input image information mediating the relationship. Performance parameters, such as entropy, mean, and standard deviation, moderate this relationship.

Input and Output		**Feature of This Solution**	**Contribution & The Value of This Work**
Input	**Output**	This solution merges multiple medical images from PET, MRI, and CT into a single image, providing accurate, informative data for clinical diagnosis using advanced algorithms like DWT and PCA.	This work presents a solution for improving clinical diagnosis accuracy, reducing data requirements, being reliable, applicable to multiple imaging modalities, and potentially gaining wider adoption, ultimately leading to improved patient outcomes and improved healthcare delivery.
Medical images from different modalities such as PET, MRI and CT.	A single fused image that provides more comprehensive and reliable data for clinical diagnosis.		

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed solution for image fusion in medical imaging, using DWT and PCA, improves diagnostic accuracy, reduces data size, is reliable, robust, and scalable. It also has potential for future research to prevent diseases in their early stages.	The proposed solution, involving complex algorithms like DWT and PCA, may be complex, costly, time-consuming, and limited in applicability, potentially limiting accessibility, cost, and applicability in certain healthcare settings, despite its potential benefits.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The proposed approach of fusing PET, CT and MRI images using DWT and PCA has a potential to improve diagnostic accuracy for severe diseases like cancer and brain tumor. However, more experimental validation and details about the evaluation metrics is needed to strengthen the paper.	Discrete wavelet transforms (DWT), Principal component analysis (PCA) and fusion metrics for evaluating the effectiveness of the image fusion.	Abstract I. Introduction II. Related Work III. Image Fusion Process IV. Parameter Test V. Result VI. Conclusion VII. Future Scope

Diagram/Flowchart



---End of Paper 8---

9		
Reference in APA format	H. Yan and Z. Li, "A Multi-modal Medical Image Fusion Method in Spatial Domain," 2019 IEEE 3rd Information Technology, Networking, Electronic and Automation Control Conference (ITNEC), Chengdu, China, 2019, pp. 597-601, doi: 10.1109/ITNEC.2019.8729143.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**

https://ieeexplore.ieee.org/document/8729143	Huibin Yan and Zhongmin Li	Multi-modal medical image fusion; spatial domain; moving frame-based decomposition framework; weight map
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
A multi-modal medical image fusion method based on multi-scale transform (MST).	The goal of the proposed solution in this paper is to develop a fast and efficient multi-modal medical image fusion method that can achieve high contrast, retain more edge and texture information, and produce fused images that are more in line with human vision. The problem that needs to be solved is the fusion of multi-modal medical images, which is important for clinical applications	1. Moving Frame Based Decomposition Framework (MFDF) for decomposing the input images into texture and approximation components. 2. Weight Map Refined Strategy based on image properties and guide filtering (GF) for fusing the texture components. 3. Approximation Component Fusion for fusing the approximation components. 4. MFDF Reconstruction for reconstructing the fused image.
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process		

The authors had adopted a moving frame-based decomposition framework to decompose source images to texture components and approximation components. In addition, the fused texture and approximation components are then combined using the MFDF Reconstruction method to obtain the final fused image.

	Process Steps	Advantage	Disadvantage (Limitation)
1	The input images are decomposed into texture and approximation components using the Moving Frame Based Decomposition Framework (MFDF).	It can separate the texture and approximation components of the input images, which is important for preserving the edge and texture information during the fusion process.	The decomposition process may introduce some artifacts and noise
2	The texture components of the input images are fused using a Weight Map Refined Strategy based on image properties and guide filtering (GF).	It can effectively preserve the edge and texture information of the input images, which is important for clinical applications.	The guide filtering -based method may under-sharpen the image details such as texture information.
3	The approximation components of the input images are fused using a simple averaging method.	It can effectively preserve the overall structure and intensity information of the input images.	It may not be able to preserve the edge and texture information of the input images.
4	The fusion texture and approximation components are combined using MFDF Reconstruction method to obtain the final fused image	It can combine the texture and approximation components to produce a high-quality fused image.	The reconstruction process may introduce some artifacts and noise.

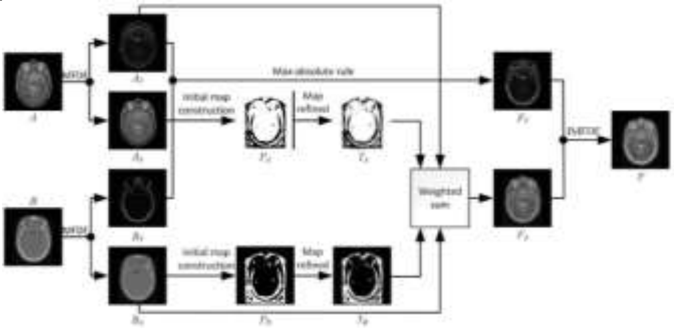
Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The quality of multi-modal medical image fusion, as measured by the effectiveness and accuracy of the proposed method in achieving promising results.	The components of the proposed method, including the moving frame-based decomposition framework and the novel weight map refined strategy based on image properties and guide filtering.	Factors that may influence the performance of the image fusion method, such as the characteristics of the input medical images, imaging modalities involved, and the complexity of the medical scenarios.	The decomposition of source images into texture and approximation components, as well as the application of the weight map refined strategy to fuse the approximation components, can be seen as intervening processes that contribute to the overall effectiveness of the image fusion.

Relationship Among the Above 4 Variables in This article
The components of the proposed method (independent variable) affect image fusion quality, with this relationship influenced by mediating processes (decomposition and weight map strategy) and moderated by external factors (input image characteristics, imaging modalities, and medical scenario complexity).

Input and Output	Feature of This Solution	Contribution & The Value of This Work
<table><tr><th>Input</th><th>Output</th></tr><tr><td>A set of multi-modal</td><td>A fused image</td></tr></table>	It achieves a quick and efficient image fusion via single-level decomposition, surpassing methods with multiple levels. By utilizing a Moving Frame Based	Contribution of this work proposes a rapid and efficient multi-modal medical image fusion method, enhancing contrast and preserving edge and texture information

<table>
<tr><td colspan="2">medical images</td><td colspan="2">Decomposition Framework, it effectively preserves edge and texture information, yielding high-contrast images that closely align with human vision, crucial for clinical applications.</td><td colspan="2">through a novel weight map refined strategy. This work has the potential to improve medical image fusion accuracy and efficiency, offering valuable applications in disease diagnosis, treatment planning.</td></tr>
<tr><th colspan="3">Positive Impact of this Solution in This Project Domain</th><th colspan="3">Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="3">The proposed method is fast and efficient, and does not have the problem of selecting the number of decomposition levels. It can achieve high contrast, retain more edge and texture information, and the fused images are more in line with human vision.</td><td colspan="3">Absence of comparative analysis with existing methods are notable weaknesses</td></tr>
<tr><th colspan="2">Analyse This Work By Critical Thinking</th><th colspan="2">The Tools That Assessed this Work</th><th colspan="2">What is the Structure of this Paper</th></tr>
<tr><td colspan="2">The multi-modal medical image fusion method holds promise with innovative techniques, but lacks detailed insight into the weight map strategy and comparative analysis with existing methods, limiting its overall robustness.</td><td colspan="2">The authors use objective evaluation metrics, including contrast (SD), gradient-based metric GQ, similarity-based metric WQ and EQ, and the visual information fidelity fusion (VIFF) metric to compare the proposed method with other state-of-the-art methods.</td><td colspan="2">Abstract
I. Introduction
II. Several Basic Theories
III. The Proposed Fusion Method
IV. Experiments and Discussion
V. Conclusion</td></tr>
<tr><th colspan="6">Diagram/Flowchart</th></tr>
</table>



---End of Paper 9--

10		
Reference in APA format	V. A. Rani and S. Lalitha Kumari, "A Hybrid Fusion Model for Brain Tumor Images of MRI and CT," 2020 International Conference on Communication and Signal Processing (ICCSP), Chennai, India, 2020, pp. 1312-1316, Doi: 10.1109/ICCSP48568.2020.9182371.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
A Hybrid Fusion Model for Brain Tumor Images of MRI and CT | IEEE Conference Publication | IEEE Xplore	V. Amala Rani and S. Lalitha Kumari	CT, image fusion, MRI, discrete wavelet transforms
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
A Hybrid Fusion Model for Brain Tumor Images of MRI and CT	Goal: Develop a hybrid image fusion technique that can effectively combine the MRI and CT images of	The proposed hybrid image fusion algorithm consists of two main components: Empirical mode

	brain to provide high quality fused images with no distortion. Problem: The manual interpretation of multimodal medical images that can be time consuming and prone to errors.	decomposition (EMD) and discrete wavelet transform (DWT).

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed model uses a hybrid image fusion technique to effectively combine the MRI and CT images of brain and provide high quality fused images with minimal or no distortion.

	Process Steps	Advantage	Disadvantage (Limitation)
1	The input MRI and CT images are decomposed into intrinsic mode function using empirical mode decomposition	Empirical mode decomposition is used as it can adapt to the local frequency characteristics of input image and preserve all the information details.	Empirical mode decomposition is sensitive to noise and artifacts in the input images and it is computationally complex.
2	The input images are decomposed into sub-bands using discrete wavelet transform.	Discrete wavelet transform can capture the global frequency characteristics of the input images and reduce noise and artifacts.	Discrete wavelet transform is sensitive to the choice of wavelet basis and its potential loss of information in the high frequency sub-bands.
3	The intrinsic mode function and sub-bands are combined using weighted average	Weighted average method balances the functional and structural information of	Weighted average method is sensitive to the choice of weighted factors and its potential

	method to obtain a fused image	the input images and reduce distortion.	loss of information in overlapping regions of input images.
4	The fused image is evaluated using various performance metrics to assess its quality and information content.	The quality and information content of the fused image is assessed.	Relying solely on performance metrics for evaluating the fused image may overlook essential contextual aspects and subjective interpretations.

Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Fused image quality: It reflects the overall quality of the fused image obtained through the EMD and DWT-based fusion method.	Empirical Mode Decomposition (EMD) of images and discrete wavelet transform (DWT) method: It represents the methods used for multimodal image fusion.	Hybrid Fusion Response: It represents the overall outcome of the proposed approach as it moderates the contribution of both EMD and DWT in the image fusion process.	Spatial Characteristics of the Original Image: The method claims to retain the spatial characteristics of the original image in the fused result, indicating a mediating role in preserving the structural information during the fusion process.
Relationship Among the Above 4 Variables in This article			

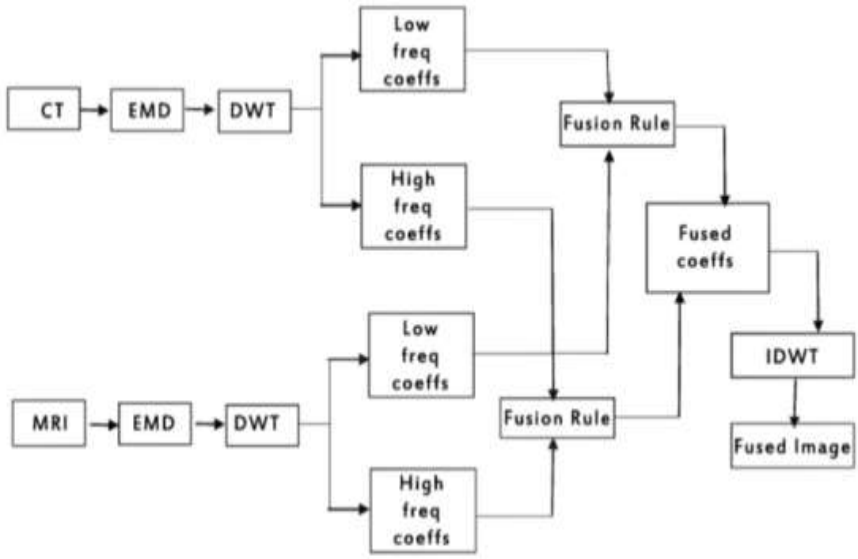
The quality of a fused image is influenced by the methods of image decomposition (EMD) and fusion (DWT), with spatial characteristics from original images contributing positively. The hybrid fusion response, which indicates the dominance of results, reflects the overall success of the fusion method.

<table>
<tr><th colspan="2">Input and Output</th><th>Feature of This Solution</th><th>Contribution in This Work</th></tr>
<tr><td>Input</td><td>Output</td><td rowspan="2">The algorithm fuses functional and structural information from MRI and CT images of the brain, enhancing accuracy through a hybrid fusion method based on empirical mode decomposition and discrete wavelet transform.</td><td rowspan="2">The contribution lies in developing a hybrid fusion algorithm merging empirical mode decomposition and discrete wavelet transform to enhance accuracy and completeness of brain image analysis, providing a comprehensive representation for improved medical diagnosis.</td></tr>
<tr><td>MRI and CT images of the brain.</td><td>A fused image and various performance metrics that evaluate quality and information content of fused image.</td></tr>
</table>

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
AI-powered medical imaging enhances diagnosis accuracy, reduces manual errors, and improves image quality across organs, revolutionizing healthcare through efficient and reliable disease detection and treatment.	The algorithm's effectiveness in medical imaging tasks depends on input image quality and task context, necessitating further research for validation across diverse datasets and addressing complex computational steps and practical implementation challenges.

Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The hybrid algorithm employing EMD and DWT for multimodal brain image fusion enhances accuracy but faces challenges related	Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR), Entropy, Standard Deviation (SD), Mutual Information	Abstract I. Introduction II. Related Works III. Proposed Work

to input quality sensitivity and computational complexity, requiring further validation for real-world applicability.	(MI), and Structural Similarity (SSIM)	IV. Experiment Results and Discussions V. Conclusion
Diagram/Flowchart		



---End of Paper 10---

11		
Reference in APA format	Kaur, M., Singh, D. Multi-modality medical image fusion technique using multi-objective differential evolution based deep neural networks. *J Ambient Intell Human Comput* 12, 2483–2493 (2021). https://doi.org/10.1007/s12652-020-02386-0	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://link.springer.com/article/10.1007/s12652-020-02386-0#citeas	Manjit Kaur & Dilbag Singh	Fusion, Diagnosis, CNN, Multi-modality, Differential evolution.
The Name of the Current Solution	**The Goal (Objective) of this Solution & What is**	**What are the components of it?**

(Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	the problem that need to be solved	
Multi-modality medical image fusion technique using multi-objective differential evolution based deep neural networks.	Goal: To fuse multi-modality medical images to obtain a more informative and accurate representation of the underlying anatomy or pathology. Problem: The challenge of integrating information from multiple imaging modalities, such as CT, MRI, and PET, which provide complementary information but have different strengths and limitations.	The proposed approach combines non-subsampled contourlet transform (NSCT) decomposition, Xception-based feature extraction, multi-objective differential evolution for feature selection, and coefficient of determination and energy loss-based fusion functions to construct superior multi-modality medical images compared to competitive methods.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Pre-processing of input images using the non-subsampled contourlet transform and other image processing techniques.	The non-subsampled contourlet transform is a powerful tool for multi-scale and multi-directional image analysis, which can help to extract more informative features from the input images.	The pre-processing step may increase the computational complexity of the overall approach and require additional computational resources.

2	Feature extraction using an extreme version of the Inception neural network architecture.	The Inception architecture is a state-of-the-art deep neural network that has been shown to be effective in various computer vision tasks, including feature extraction from medical images.	The use of a deep neural network for feature extraction may require significant computational resources and may be sensitive to the choice of hyper-parameters.
3	Feature selection using a multi-objective differential evolution algorithm.	The multi-objective differential evolution algorithm is a powerful optimization technique that can help to select the most informative features from the input images, which can improve the accuracy and efficiency of the overall approach.	The feature selection step may require extensive hyper-parameter tuning and may be sensitive to the choice of optimization algorithm.
4	Fused coefficient computation using coefficient of determination and energy loss based fusion functions.	The use of coefficient of determination and energy loss based fusion functions can help to combine the most informative features from the input images and obtain a more accurate and informative representation of the underlying anatomy or pathology.	The choice of fusion functions may affect the performance of the overall approach and may require extensive experimentation and validation.
5	Fused image computation using the inverse non-subsampled contourlet transform.	The inverse non-subsampled contourlet transform can help to reconstruct the fused image	The inverse non-subsampled contourlet transform may be computationally complex

		from the fused coefficients and obtain a more informative and accurate representation of the underlying anatomy or pathology.	and require significant computational resources.

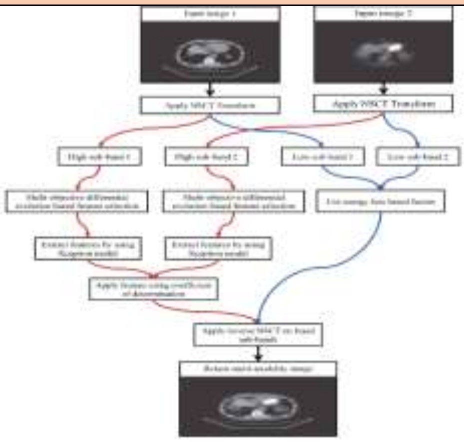
Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
The quality of the resulting fused image obtained through the proposed approach, serving as the dependent variable.	proposed Multi-modality Image Fusion Approach Represents the innovative technique utilized for combining information from different medical images, acting as the independent variable.	Multi-objective Differential Evolution optimization algorithm moderates the relationship between the independent variable (proposed approach) and the dependent variable (fused image quality), aiding in the selection of optimal features.	Feature Extraction Using Extreme Inception (Xception) Plays a mediating role in the relationship between the proposed approach and fused image quality, as it extracts relevant features from the source images.

Relationship Among The Above 4 Variables in This article
The proposed Multi-modality Image Fusion Approach is influenced by Feature Extraction using Xception, moderated by Multi-objective Differential Evolution, resulting in enhanced Fused Image Quality, outperforming other multi-modality fusion methods.

Input and Output	**Feature of This Solution**	**Contribution & The Value of This Work**

<table>
<tr>
<td><table><tr><th>Input</th><th>Output</th></tr><tr><td>medical images</td><td>multi-modality medical images</td></tr></table></td>
<td colspan="2">The proposed solution is a multi-modality medical image fusion approach that combines deep neural networks and optimization algorithms to obtain informative and accurate representations of the underlying anatomy or pathology.</td>
<td>A multi-objective differential evolution and Xception model based multi-modality biomedical fusion model is proposed.

The value of this work lies in its ability to provide a more accurate and informative representation of the underlying anatomy or pathology in multi-modality medical images</td>
</tr>
<tr>
<th colspan="2">Positive Impact of this Solution in This Project Domain</th>
<th colspan="2">Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td colspan="2">The positive impact of this work is that it can help medical professionals to make more informed decisions and improve patient outcomes.</td>
<td colspan="2">The use of advanced image processing techniques, especially in the medical field, raises concerns about patient privacy and data security, requiring careful handling of sensitive information.</td>
</tr>
<tr>
<th>Analyse This Work By Critical Thinking</th>
<th colspan="2">The Tools That Assessed this Work</th>
<th>What is the Structure of this Paper</th>
</tr>
<tr>
<td>The proposed advanced multi-modality image fusion approach, integrating NSCT and Xception, presents promising diagnostic enhancements, but critical considerations include computational complexity, interpretability challenges, and the need for transparent</td>
<td colspan="2">TensorFlow or PyTorch for Xception,numpy and scipy.</td>
<td>1) Abstract
2) Introduction
3) Literature Review
4) Experimental Analysis
5) Conclusion
6) References</td>
</tr>
</table>

reporting on datasets and ethical considerations for robust real-world application.		
Diagram/Flowchart		
		

---End of Paper 11---

12		
Reference in APA format	L. Wang, J. Zhang, Y. Liu, J. Mi and J. Zhang, "Multimodal Medical Image Fusion Based on Gabor Representation Combination of Multi-CNN and Fuzzy Neural Network," in IEEE Access, vol. 9, pp. 67634-67647, 2021, Doi: 10.1109/ACCESS.2021.3075953.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
[Multimodal Medical Image Fusion Based on Gabor Representation Combination of Multi-CNN and Fuzzy Neural Network | IEEE]()	Lifang wang, Jin Zhang, Yang Liu, Jia Mi, Jiong Zhang	Medical image fusion, G-CNNs, Gabor representation, convolutional neural network, fuzzy neural network.

Journals & Magazine | IEEE Xplore		
The Name of the Current Solution (Technique/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Multimodal Medical Image Fusion Based on Gabor Representation Combination of Multi-CNN and Fuzzy Neural Network.	Goal: To improve the quality of multimodal medical image fusion Problem: to effectively integrate the rich texture features and clear edge information of different modalities into a single fused image to get accurate information.	Author used Gabor representation, multi-CNNs and fuzzy neural networks for obtaining fused images.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed model integrates rich texture feature and clear edge information, enhancing the quality of medical image fusion and assists doctors in disease diagnosis by providing a fused image that combines useful information from multiple modalities.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Gabor filter banks are used to obtain Gabor representation of CT and MR images, capturing complex textures and edge information. These filtered images are used to train 16 corresponding CNNs.	Gabor representations have multiple detail texture and edge information int different directions and scales to enhance the texture feature of the source images.	Gabor representation may increase computational complexity.

2	Fuzzy neural network effectively fuses the outputs of G-CNNs, improving image fusion quality.	The fuzzy neural network effectively fuses the outputs of G-CNNs, leading to improve image fusion quality.	A Fuzzy neural network may require more training data and longer training time.
3	The proposed fusion method is compared with nine recent state-of-the-art multimodal fusion methods using mutual information, spatial frequency, standard deviation, and edge retention information.	Objective evaluation provides quantitative measures of performance. Comparative analysis helps assess the proposed method against existing approaches.	The performance comparison may depend on the datasets used for evaluation. Sensitivity to metric choice: Different metrics may provide varying perspectives on the method's performance.

Major Impact Factors in this Work

<Find all main factors and variables that are related to each solution. Then find the relationship between factors. (Independent variable) causes a change in (Dependent Variable) and it isn't possible that (Dependent Variable) could cause a change in (Independent Variable).

Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Fused image quality (Performance metrics): It is assessed using various performance metrics like mutual information, spatial frequency, standard deviation, and edge	Gabor representation of multi-CNN combination: It represents the use of Gabor filters and convolutional neural networks to process and extract features from CT and MRI images.	G-CNNs: They acts as mediating variable between Gabor representation and Fused image quality as they are trained to generate preliminary fusions of Gabor representations.	Fuzzy neural network: It takes multiple outputs from G-CNNs and fuses them to obtain the final fused image. It moderates the contribution of individual G-CNNs to enhance the

retention information.			overall fused image quality.

Relationship Among the Above 4 Variables in This article
The process involves training G-CNNs using CT and MR images, which are then fused by a fuzzy neural network. The final fused image quality is influenced by the performance of the G-CNNs, which are then further processed by the network. This improvement in fused image quality enhances medical image fusion, aiding in disease diagnosis.

Input and Output		Feature of This Solution	Contribution & The Value of this Work
Input	**Output**		
CT and MR images of brain.	Identification of brain tumor disease in the fused image to determinate grade and boundary of brain tumor.	It outperforms nine recent states of the art multimodal fusion methods in terms of average mutual information, spatial frequency, standard deviation, and edge retention information.	Categorizing complex textures and edge information of lesion in the fused image contributes to the field of multimodal medical image fusion.

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The method outperforms other fusion methods in objective evaluation and visual quality, with significant improvements, spatial frequency, standard deviation and edge retention information.	

Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The proposed method effectively combines Gabor representation, multi-CNNs, and fuzzy neural network to enhance the quality of fused images, providing valuable assistance in disease diagnosis.	The proposed method is evaluated using quantitative metrics to measure various aspects of fused images, comparing it to other advanced fusion methods.	Abstract I. Introduction II. Related work III. Multimodal medical image fusion based on the combination of G-CNNs and Fuzzy neural network IV. Experimental results and analysis V. Conclusion

Diagram/Flowchart

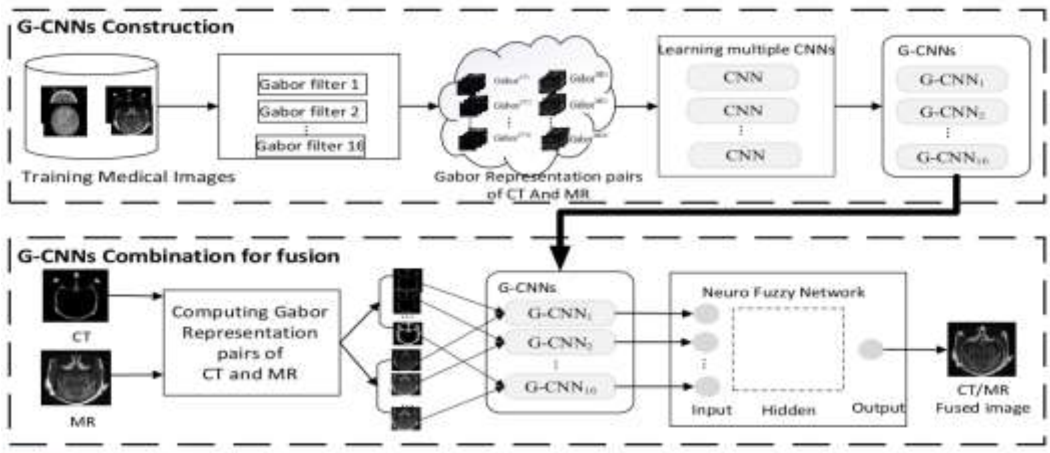


FIGURE 2. Multimodal medical image fusion process based on G-CNNS and fuzzy neural network.

---End of Paper 12---

13	
Reference in APA format	C. Gao, C. Song, Y. Zhang, D. Qi and Y. Yu, "Improving the Performance of Infrared and Visible Image Fusion Based on Latent Low-Rank Representation Nested with Rolling Guided Image

	Filtering," in IEEE Access, vol. 9, pp. 91462-91475, 2021, doi: 10.1109/ACCESS.2021.3090436.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/9459693	C. Gao, C. Song Ce Gao	Feature extraction, Image fusion, Image edge detection, Information filters, Image reconstruction, Frequency measurement
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
Improving the Performance of Infrared and Visible Image Fusion Based on Latent Low-Rank Representation Nested With Rolling Guided Image Filtering	Objective: To improve the performance of infrared and visible image fusion by using a novel method that combines LatLRR (Latent Low-Rank Representation) with RGIF (Recursive Guided Image Filtering). The problem that needs to be solved is improving the performance of infrared and visible image fusion methods in terms of image contrast, sharpness, and richness of detailed information.	The proposed method for infrared and visible image fusion consists of five components: image decomposition, acquisition of a detail-enhanced layer, fusion of low-rank sublayers, fusion of saliency sublayers, and image reconstruction. These components work together to enhance image contrast, sharpness, and richness of detailed information.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process
the proposed method shows promising results in terms of preserving image details, contrast, and overall structural similarity. However, there are still some areas where further improvements can be made to address the limitations mentioned above.

	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	, the input image is smoothed using a Gaussian filter to remove small structures. The smoothed image is then used as a guidance image for the next step.	It can effectively preserve texture detail information, resulting in sharper and more distinct features in the fused image. It also provides high contrast and good overall structural similarity between the fused image and the source image. Additionally, the proposed method can preserve rich and effective information, making it suitable for various types of image processing tasks.	While the proposed method has many advantages, there are also some limitations. In certain cases, such as the fusion of images with tree canopies or figures, artifacts may appear on the edges of the contours. The fused images may also have less contrast information compared to other methods. Additionally, the sky background of the fused image may appear dark, affecting the acquisition of information.
2	edge recovery is performed through an iterative operation using an edge-preserving filter such as guided image filtering (GIF)	it can handle non-linear deformations	increased computational complexity.

	or the weighted least squares filter.		

Major Impact Factors in this Work

The proposed method in this work has the highest average values for six objective evaluation metrics: EN, MI, MS_SSIM, Qabf, SCD, and SD. It also has the third highest average values for two other metrics: AG and VIF.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable

Relationship Among The Above 4 Variables in This article

Input and Output		Feature of This Solution	Contribution & The Value of this Work
Input	**Output**	The proposed fusion method uses LatLRR with denoising and local structure representation capabilities for image decomposition, nested with RGIF for image enhancement. It employs a two-level decomposition and three-layer fusion approach, allowing for flexible fusion of infrared and visible images.	This study presents a novel approach utilizing two-level decomposition and three-layer fusion with LatLRR nested within RGIF to enhance infrared and visible image fusion, addressing existing method limitations. It outperforms state-of-the-art fusion techniques, demonstrating superior results across six objective evaluation metrics, indicating improved image quality and information preservation.
An image	The reconstructed fused image		

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
The proposed method for infrared and visible image fusion based on LatLRR nested with RGIF has shown positive impact in terms of preserving rich and effective information, providing high contrast, and producing a good overall structural similarity between the fused image and the source image. It has also demonstrated improvements in image contrast, sharpness, and richness of detailed information compared to other fusion methods.	Limited improvement in image sharpness and richness: While the proposed method aims to improve image contrast, sharpness, and richness of detailed information, the comparison of fusion methods suggests that there is still room for improvement in these aspects. This indicates that the proposed method may not fully address the challenges in the project domain related to image quality enhancement.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
The proposed method demonstrates improvements in infrared and visible image fusion by effectively preserving texture detail information, enhancing image sharpness and contrast, and achieving good fusion performance. The combination of LatLRR and RGIF proves to be a promising approach for image fusion.	information entropy (EN), mutual information (MI), multiscale structural similarity (MS-SSIM), standard deviation (SD), average gradient (AG), edge-based similarity (Qabf), sum of the correlations of differences (SCD), and visual information fidelity (VIF).	I. Introduction II. Technical Background III. Proposed Fusion Method IV. Experimental Results and Analysis V. Conclusion

Diagram/Flowchart

---End of Paper 13---

14		
Reference in APA format	X. Fu, L. Bi, A. Kumar, M. Fulham and J. Kim, "Multimodal Spatial Attention Module for Targeting Multimodal PET-CT Lung Tumor Segmentation," in IEEE Journal of Biomedical and Health Informatics, vol. 25, no. 9, pp. 3507-3516, Sept. 2021, Doi: 10.1109/JBHI.2021.3059453.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
Multimodal Spatial Attention Module for Targeting Multimodal PET-CT Lung Tumor Segmentation | IEEE Journals & Magazine | IEEE Xplore	Xiaohang Fu, Lei Bi, Ashnil Kumar, Michael Fulham and Jinman Kim	Convolutional Neural Network (CNN), Multimodal Image Segmentation, Positron Emission Tomography-Computed Tomography (PET-CT)
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Multimodal Spatial Attention Module for Targeting Multimodal PET-CT Lung Tumor Segmentation	Goal: To improve the accuracy of tumor segmentation in PET-CT images using a deep-learning based framework with a multimodal special attention module. Problem: The challenge of accurately identifying	The proposed deep learning framework uses a multimodal spatial attention module and a convolutional neural network backbone to segment PET-CT images, focusing on tumor-related regions.

	tumor regions in PET-CT images.	

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed framework consists of several steps, each with its advantages and disadvantages:

	Process Steps	Advantage	Disadvantage (Limitation)
1	Preprocessing the PET-CT images to remove noise, artifacts and normalize intensity values.	It can improve the accuracy of the segmentation results.	It can be computationally expensive.
2	Using a CNN backbone to learn the features of the input image and generate an initial segmentation map.	It can capture complex spatial and temporal relationships in the input data and generate accurate segmentation maps.	It can be sensitive to noise and artifacts in the input data, which can affect the accuracy of the segmentation results.
3	Using a multimodal spatial attention module to refine the segmentation map generated by CNN backbone.	It can improve the accuracy of the segmentation results by focusing on tumor region.	It can be computationally expensive and may require a large amount of training data to achieve optimal performance.
4	Evaluating the accuracy of the segmented results using Dice similarity coefficient metrics.	It provides a quantitative measure foe the accuracy of the segmentation results.	It may not capture all aspects of segmentation performance.

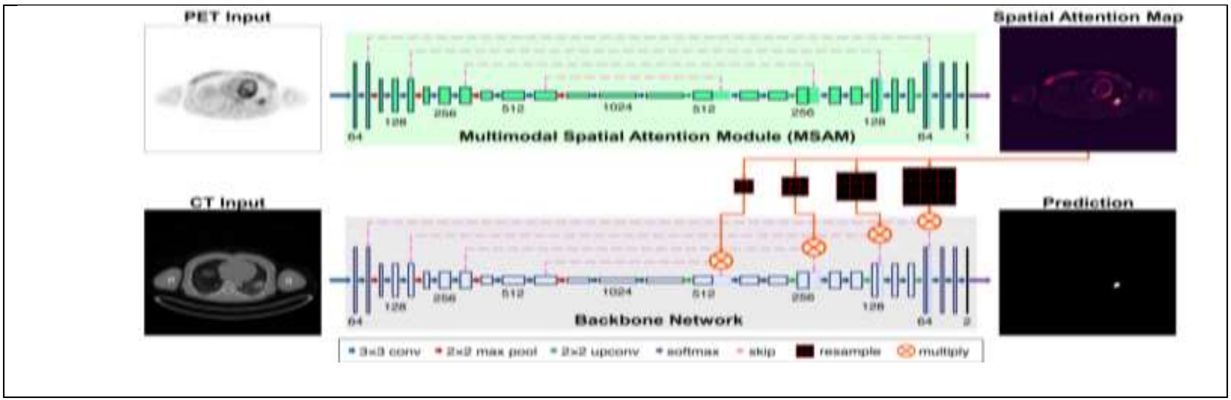
Major Impact Factors in this Work

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Effectiveness of Multimodal PET-CT Segmentation: It is influenced by the use of the MSAM in the segmentation process.	Multimodal spatial attention module: It learns to emphasize regions related to tumor and suppress normal regions with physiologic high uptake from the PET input.	Type of cancer: The experimental results are conducted on PET-CT datasets of different cancer types, indicating that the performance may vary across different cancer types.	Spatial attention maps: The MSAM generates spatial attention maps that automatically emphasize regions related to tumors and suppress normal regions.

Relationship Among the Above 4 Variables in This article
The MSAM directly influences the effectiveness of multimodal PET-CT segmentation, mediating the creation of spatial attention maps that guide the CNN backbone. The type of cancer may moderate this relationship, affecting segmentation performance.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	**Output**	The proposed solution uses PET and CT modalities for improved tumor segmentation accuracy. It can handle varied anatomical and functional features. The framework outperforms state-of-the-art methods in segmentation accuracy.	This work presents a significant improvement in tumor segmentation in PET-CT images. It outperforms existing methods, utilizes PET sensitivity, handles varied anatomical and functional features, and has the potential to improve patient care.
A multimodal PET-CT image, which consists of PET and CT image.	A segmentation map that identifies tumor regions in the image.		

<table>
<tr><th colspan="2">Positive Impact of this Solution in This Project Domain</th><th colspan="2">Negative Impact of this Solution in This Project Domain</th></tr>
<tr><td colspan="2">The proposed solution improves tumor delineation accuracy, aiding in diagnosis, treatment planning, and personalized medicine. This could enhance clinical practice, reduce manual segmentation, and improve patient care.</td><td colspan="2">The proposed solution faces potential negative impacts, including overfitting, computational requirements, limited generalizability, and reliance on high-quality images which could affect the accuracy and reliability, and may affect the applicability of the framework to specific patient populations.</td></tr>
<tr><th>Analyse This Work by Critical Thinking</th><th colspan="2">The Tools That Assessed this Work</th><th>What is the Structure of this Paper</th></tr>
<tr><td>The paper proposes a deep learning-based system for multimodal PET-CT segmentation which uses CNN and a multimodal spatial attention module. Using two PET-CT datasets, the study assessed the framework and compared it to cutting-edge techniques. Despite certain drawbacks, it makes a substantial addition to the field of medical picture analysis.</td><td colspan="2">A deep learning-based framework for multimodal PET-CT segmentation using TensorFlow.</td><td>Abstract
I. Introduction
II. Methods
III. Results
IV. Discussion
V. Conclusion</td></tr>
<tr><th colspan="4">Diagram/Flowchart</th></tr>
</table>



---End of Paper 14---

15

Reference in APA format	K. Kusram, S. Transue and M. -H. Choi, "Two-Phase Multimodal Image Fusion Using Convolutional Neural Networks," 2021 IEEE International Conference on Image Processing (ICIP), Anchorage, AK, USA, 2021, pp. 1874-1878, doi: 10.1109/ICIP42928.2021.9506703.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://ieeexplore.ieee.org/document/9506703	Ch. Hima Bindu, K. Veera Swamy	Coarse Fusion Network (CFN), Refining Fusion Network (RFN), Depth and Thermal Synchronized Streams, Image-space Transformations
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
Two-phase multimodal image fusion using convolutional neural networks	Goal: To present a novel method for fusing multiple imaging modalities at a per-pixel level. By employing a	The components of the proposed solution include a hypergraph-based manifold regularization, a multi-modal

	two-phase non-linear registration method. Problem: The fusion of multiple imaging modalities at a per-pixel level, is challenging due to the variations in sensor and lens intrinsics. Traditional calibration methods have limitations in achieving accurate alignment.	feature selection method, and a multi-task multi-linear regression model for predicting cognitive scores. The solution also involves integrating SNP, DNA methylation, and functional magnetic resonance imaging (fMRI) data to improve classification accuracy and biomarker detection.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed MS-DAYOLO framework improves the robustness and accuracy of object detection in cross-domain scenarios, making it a promising solution for real-world applications.

	Process Steps	Advantage	Disadvantage (Limitation)
1	This is the first stage of the proposed method, where a shared feature space is used to perform a global rigid alignment of the input images.	It reduces the computational complexity of the registration process.	it may not be able to handle non-linear deformations.
2	This is the second stage of the proposed method, where per-pixel displacements are predicted to refine the alignment obtained in the first stage.	it can handle non-linear deformations	increased computational complexity.

3	The proposed method assumes the provision of depth and thermal images that are synchronized for training. Image-space transformations are used to generate training data for the CFN and RFN.		
4	Edge-based correspondence methods such as CPD and ICP are used to generate training data for the CFN. Dense optical flow is used to generate training data for the RFN. The RFN predicts per-pixel displacements that are used to refine the alignment obtained in the first stage		
5.	The proposed method achieves a per-pixel level fusion of the input images, resulting in an efficient and accurate image registration. The proposed method requires a large amount of training data to achieve accurate registration.		

Major Impact Factors in this Work
This work proposes a novel method for multimodal image fusion using convolutional neural networks, which achieves an increase of 18% in average accuracy over global registration. The

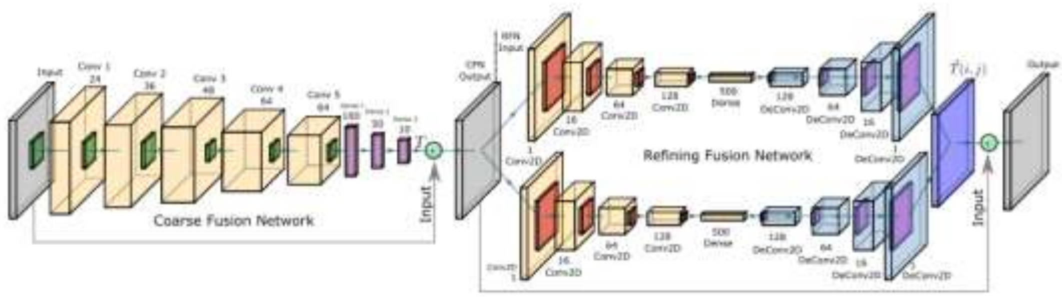
method involves a two-phase non-linear registration method that performs per-pixel transformations.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable in this work is the accuracy of image registration, which is measured using displacement error calculated using Hausdorff distance. The goal is to minimize this distance as much as possible.	The independent variables in this work are the input and expected data during training, which include depth and thermal data integrated into spatial point-cloud data. The method also involves a two-phase non-linear registration method that performs per-pixel transformations.	moderating variable in this work is the focus is on developing a novel method for multimodal image fusion using convolutional neural networks.	The study focuses on the focus is on developing a novel method for multimodal image fusion using convolutional neural networks.

Relationship Among The Above 4 Variables in This article
the relationship among mediating (intervening) variables, moderating variables, dependent variables, and independent variables. The study focuses on optimizing the multi-modal image fusion architecture for medical image segmentation, with the segmentation accuracy as the dependent variable and the multi-modal image fusion architecture as the independent variable. The study does not examine the underlying mechanisms or processes that may mediate or moderate the relationship between the input images and the segmentation output.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td><table><tr><th>Input</th><th>Output</th></tr><tr><td>The input of the paper is the development of a two-phase multimodal image fusion method using convolutional neural networks.</td><td>The output is a fused image that combines multiple imaging modalities at a per-pixel level, resulting in an efficient and accurate image registration.</td></tr></table></td>
<td colspan="2">the feature of this solution is its ability to fuse multiple imaging modalities at a per-pixel level using a two-phase non-linear registration method, resulting in an efficient and accurate image registration.</td>
<td>The contribution of this work is the development of a deep learning-based approach for multimodal image fusion that outperforms traditional calibration methods. The value of this work lies in its potential to improve machine vision applications that require accurate image registration, such as medical imaging and autonomous driving.</td>
</tr>
<tr>
<th colspan="2">Positive Impact of this Solution in This Project Domain</th>
<th colspan="2">Negative Impact of this Solution in This Project Domain</th>
</tr>
<tr>
<td colspan="2">the positive impact of this solution in the project domain is the potential to improve the accuracy and efficiency of machine vision applications that require multimodal image fusion, such as facial authentication, autonomous vehicles, remote sensing, medical imaging, and environmental reconstruction.</td>
<td colspan="2">the negative impact of this solution. However, it is possible that the implementation of this solution may require significant computational resources, which could be a potential limitation for some applications. Additionally, the accuracy of the method may be affected by factors such as image distortion and resolution, which could impact its performance in certain scenarios.</td>
</tr>
<tr>
<th>Analyse This Work By Critical Thinking</th>
<th colspan="2">The Tools That Assessed this Work</th>
<th>What is the Structure of this Paper</th>
</tr>
</table>

the authors present a promising approach to multimodal image fusion using deep learning techniques, which could have significant implications for a wide range of applications in machine vision.	deep learning frameworks, image processing libraries, and statistical analysis tools	I. abstract II. Introduction III. Related Work IV. Experiments V. Conclusion
Diagram/Flowchart		
		

---End of Paper 15---

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Reference in APA format	Barrett, J., & Viana, T. (2022). EMM-LC Fusion: Enhanced Multimodal Fusion for Lung Cancer Classification. *AI*, *3*(3), 659–682. https://doi.org/10.3390/ai3030038	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.mdpi.com/2673-2688/3/3/38	James Barrett and Thiago Viana	Lung cancer, Diagnosis, Machine learning, classification, multimodal, fusion.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**

Model/ Tool/ Framework/ ... etc)		
Enhanced Multimodal Fusion for Lung Cancer Classification.	Enhanced lung cancer classification using multimodal fusion.	Pre-processing, feature extraction from pre trained Aligned eXception network. Fusion of multiple modalities using a deep neural network. Training of deep neural networks using extracted features. Evaluation evaluation of the trained model using various evaluation metrics such as sensitivity, specificity, accuracy, and F1 score.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

	Process Steps	Advantage	Disadvantage (Limitation)
1	Pre-processing involves standard techniques for pre-processing CT scans, such as thresholding, binarization, and morphological operations.	Noise reduction, improved contrast, and better feature extraction.	Potential loss of information and the need for careful selection of parameters.
2	Extraction of intermediate features from a pre-trained Aligned Xception network.	Ability to capture high-level features and reduce the dimensionality of the data.	Need for careful selection of features.
3	Fusion of multiple modalities using a deep neural network architecture.	Ability to combine complementary information from different	Potential for overfitting and the need for careful

		modalities and improve the accuracy of the model.	selection of fusion methods.
4	Training of the deep neural network using the extracted features and fusion approach.	Learn complex patterns and improve the accuracy of the model.	
5	Evaluation of the trained model using various evaluation metrics such as sensitivity, specificity, accuracy, and F1 score.	Ability to assess the performance of the model and compare it to other models.	

Major Impact Factors in this Work

<Find all main factors and variables that are related to each solutions. Then find the relationship between factors. (Independent variable) causes a change in (Dependent Variable) and it isn't possible that (Dependent Variable) could cause a change in (Independent Variable).

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
Lung Cancer Classification Performance Metrics Like F1 score, average precision, AUC are dependent on the application of the EMM-LC Fusion model	EMM-LC Fusion Model is the primary factor that is manipulating in this study. It represents the intervention or treatment designed to improve lung cancer detection.	Previous Fusion Method variable moderates the relationship between the independent variable (EMM-LC Fusion) and the dependent variables (Lung Cancer Classification Performance Metrics).	Intermediate Features act as a mediator between the EMM-LC Fusion model and its impact on lung cancer classification performance.

Relationship Among the Above 4 Variables in This article
EMM-LC Fusion model (independent variable) affects lung cancer classification performance metrics (dependent variables) through the mediating role of intermediate features. The influence of the previous fusion method (moderating variable) on this relationship is considered, providing insights into the specific conditions under which the EMM-LC Fusion model performs better than the previous method.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	**Output**	The use of a multimodal fusion approach that combines information from multiple modalities, including CT scans and clinical data, to improve the accuracy of lung cancer detection.	Contributes to the field of lung cancer detection by proposing a novel approach that leverages multiple sources of information and advanced machine learning techniques to improve the accuracy of diagnosis.
Set of pre-processed CT scans of the lung.	Classification of the CT scan as either malignant or benign.		

Positive Impact of this Solution in This Project Domain	Negative Impact of this Solution in This Project Domain
It's potential to significantly improve the accuracy of lung cancer detection.	It is important to carefully consider the potential benefits and limitations of the approach in the context of specific healthcare settings and patient populations.

Analyse This Work by Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper

This provides a valuable contribution to lung cancer detection. It is important to carefully consider the potential benefits and limitations of the approach in the context of specific healthcare settings and patient populations.	EMM-LC model, performance metrics like F1 score, AP, AUC.	1) Abstract 2) Introduction 3) Literature Review 4) Materials and Methods 5) Implementation 6) Results 7) Discussion 8) Limitations 9) Future Work 10) Conclusions

Diagram/Flowchart

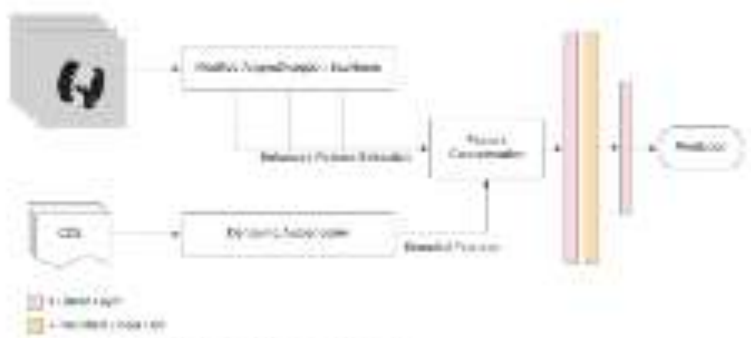


Figure 1. Model architecture schematic

---End of Paper 16--

17		
Reference in APA format	Y. Zhang, H. Zhang, L. Xiao, Y. Bai, V. D. Calhoun and Y. -P. Wang, "Multi-Modal Imaging Genetics Data Fusion via a Hypergraph-Based Manifold Regularization: Application to Schizophrenia Study," in IEEE Transactions on Medical Imaging, vol. 41, no. 9, pp. 2263-2272, Sept. 2022, doi: 10.1109/TMI.2022.3161828.	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**

https://ieeexplore.ieee.org/document/9740146	Y. Zhang, H. Zhang	Data integration, Data models, Imaging, Manifolds, Feature extraction, Genetics, Multitasking
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that needs to be solved**	**What are the components of it?**
Multi-Modal Imaging Genetics Data Fusion via a Hypergraph-Based Manifold Regularization: Application to Schizophrenia Study	The goal of this solution is to develop a novel algorithm called HMF that combines information from diverse sources for improved accuracy in diagnosing complex brain disorders. The problem that needs to be solved is the accurate diagnosis of complex brain disorders by integrating information from multiple imaging and genetics data types.	The components of the proposed solution include a hypergraph-based manifold regularization, a multi-modal feature selection method, and a multi-task multi-linear regression model for predicting cognitive scores. The solution also involves integrating SNP, DNA methylation, and functional magnetic resonance imaging (fMRI) data to improve classification accuracy and biomarker detection.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The proposed MS-DAYOLO framework improves the robustness and accuracy of object detection in cross-domain scenarios, making it a promising solution for real-world applications.

	Process Steps	Advantage	Disadvantage (Limitation)

1	This step involves defining a hypergraph-based similarity matrix to better characterize high-order structural relationships between subjects than a simple graph representation.	it can incorporate both structural information and complex interactions among subjects, which can circumvent the overfitting problem in high dimension but low sample data.	it may require more computational resources and time.
2	This step involves jointly learning common features from multi-modal data to extract more discriminative features and improve classification accuracy.	it can integrate complementary information from multiple data types, resulting in better performance compared to several existing models.	it may require more complex algorithms and may be more difficult to interpret the results.
3	This step involves predicting cognitive scores using a multi-task multi-linear regression model.	it can predict multiple cognitive scores simultaneously, which can save time and resources.	it may require more data and may be more complex to implement.
4	This step involves integrating information from multiple data types to improve classification accuracy and biomarker detection.	it can provide a more comprehensive understanding of the disease and its underlying mechanisms.	it may require more data and may be more complex to implement.

Major Impact Factors in this Work
This work introduces a novel algorithm called HMF that combines information from diverse sources for improved accuracy in diagnosing complex brain disorders, using hypergraph-based manifold regularization to capture high-order relationships among subjects and validate the approach on both synthetic data and real samples from a schizophrenia study.

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The dependent variable in this study is the authors used multi-modal data fusion to identify biomarkers and improve understanding of the disorder.	The independent variable in this paper is the proposed hypergraph-based multi-modal data fusion method, HMF. The authors used HMF to integrate imaging and genetics datasets and identify risk genes and abnormal brain regions associated with schizophrenia.	The study focuses on the authors focused on developing and validating the HMF method for multi-modal data fusion in the context of schizophrenia diagnosis.	The study focuses on the authors focused on developing and validating the HMF method for multi-modal data fusion in the context of schizophrenia diagnosis.

Relationship Among The Above 4 Variables in This article
the relationship among mediating (intervening) variables, moderating variables, dependent variables, and independent variables. The study focuses on optimizing the multi-modal image fusion architecture for medical image segmentation, with the segmentation accuracy as the dependent variable and the multi-modal image fusion architecture as the independent variable. The study does not examine the underlying mechanisms or processes that may mediate or moderate the relationship between the input images and the segmentation output.

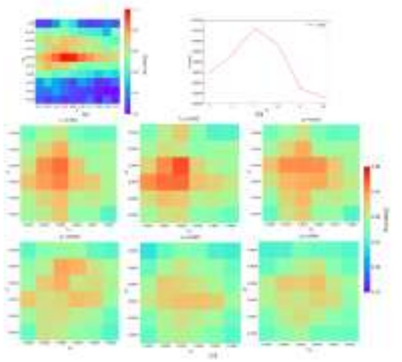
Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	Output	This solution introduces a novel algorithm called HMF that combines information from diverse sources for improved accuracy in diagnosing complex brain disorders. The method	The contributions of this work include combining complementary information from multi-modal data, defining a hypergraph-based
The input used in this research paper	The output is the validate their approach on		

includes imaging and genetics datasets. The paper introduces a novel algorithm called HMF that combines information from these diverse sources for improved accuracy in diagnosing complex brain disorders.	both synthetic data and real samples from a schizophrenia study and show that HMF outperforms several competing methods.	uses a hypergraph-based manifold regularization to capture high-order relationships among subjects and enforce regularization based on both inter- and intra-modality relationships.	similarity matrix to better characterize high-order structural relationships, employing a novel manifold regularization term to incorporate structural information both within and across modalities, and incorporating both sparsity and manifold regularization to circumvent the overfitting problem. The value of this work lies in its potential to improve the accuracy of diagnosing complex brain disorders and identify potential biomarkers associated with these disorders, which could lead to better treatment and management strategies for patients.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The positive impact of this solution in this project domain is that it provides a more accurate and comprehensive approach to	one potential limitation is that the algorithm is still based on linear regression and may not capture the complex non-linear

diagnosing complex brain disorders by integrating information from multiple sources. This can lead to better treatment and management strategies for patients and potentially identify new biomarkers associated with these disorders.	relationship between imaging genomics markers and phenotypes.

Analyse This Work By Critical Thinking	The Tools That Assessed this Work	What is the Structure of this Paper
the authors used various statistical and machine learning tools to develop and validate their algorithm, including hypergraph-based manifold regularization, multiple regression, and false discovery rate (FDR) analysis. They also compared their method with several other competing models, including MTL, SNF-SVM, MMN, gCAM-CCL, MRMF, and GSSL, using a 10-fold cross-validation approach.	false discovery rate (FDR), MTL, SNF-SVM, MMN, gCAM-CCL, MRMF, and GSSL	I. Introduction II. Methods III. Results IV. Discussion V. Conclusion

Diagram/Flowchart


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18		
Reference in APA format	Das, K. P., & Chandra, J. (2022). Multimodal Classification on PET/CT Image Fusion for Lung Cancer: A Comprehensive Survey. ECS Transitions, 107(3649).	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://iopscience.iop.org/article/10.1149/10701.3649ecst/pdf	Kaushik Pratim Das and Chandra J	PET&CT imaging, Medical image fusion, Lung cancer diagnosis, Multimodalarity imaging
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Multimodal Classification on PET/CT Image Fusion for Lung Cancer	The goal of medical image fusion is to combine multiple medical images to produce a single image that contains more comprehensive and accurate information. This is done to overcome the limitations of individual medical images and improve the accuracy and reliability of medical diagnosis and treatment.	multiple medical images, image registration techniques, image fusion algorithms, and image quality assessment methods.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process			
	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Image acquisition	improved accuracy of diagnosis due to complementary information from different modalities.	Need for specialized equipment.
2	Image registration	Improved accuracy of diagnosis due to precise spatial alignment.	Need for computationally intensive algorithms.
3	Feature extraction	Extraction of relevant information from the images, such as texture, shape, and intensity.	Need for domain expertise.
4	Image fusion	Creation of a single, fused image that contains all the relevant information from each modality.	Need for careful selection of fusion algorithms.

Major Impact Factors in this Work			
Dependent Variable	**Independent Variable**	**Moderating variable**	**Mediating (Intervening) variable**
Efficiency of Medical Image Fusion: The effectiveness and efficiency of the medical image fusion	Medical Image Fusion Techniques are the primary factor manipulated or investigated in the study. It represents	Clinical Setting Challenges associated with medical image fusion in a clinical setting, such as time	Deep Learning Techniques: This variable plays a mediating role in the relationship between medical image fusion

techniques, measured in terms of accuracy, speed, and clinical applicability. Image Quality: The quality of the fused images, assessing how well the fusion techniques preserve essential clinical information while enhancing overall image quality	the diverse methods and technologies employed for fusing medical images, specifically focusing on PET and CT imaging for lung cancer diagnosis.	consumption and technical complexity.	techniques and their impact.

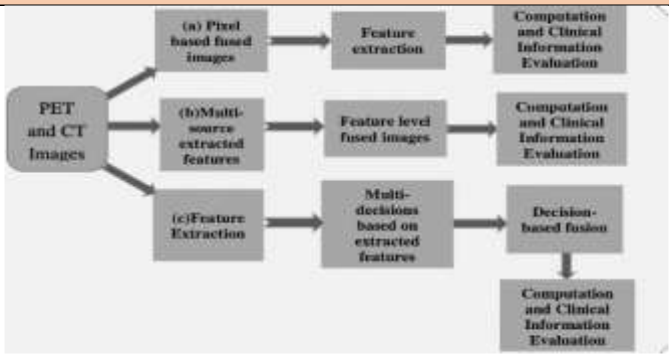
Relationship Among the Above 4 Variables in This article
The efficiency of medical image fusion techniques is influenced by the incorporation of deep learning methods. Deep learning acts as a mediator, enhancing the overall performance of fusion techniques. Challenges in a clinical setting, such as time consumption and technical complexity, moderate the impact of medical image fusion techniques on efficiency and image quality

Input and Output		**Feature of This Solution**	**Contribution in This Work**
Input	**Output**	Comprehensive coverage of medical image fusion techniques for lung cancer diagnosis, including recent advances and the impact of deep learning techniques.	The authors' work provides a valuable resource for researchers, medical professionals, and anyone interested in medical image fusion for lung cancer diagnosis.
Multiple PET and CT images	Classified Lung cancer multimodal images		

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**

This solution has the potential to make a positive impact on the field of medical imaging and improve patient outcomes in the domain of lung cancer diagnosis and treatment.	Registering images from different modalities can introduce errors, leading to misalignment of anatomical structures.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
The provided information is very useful and the detailed explanation of process helps to build efficient model.	TensorFlow or PyTorch, openCv	1) Abstract 2) Introduction 3) Literature Review 4) Discussions 5) Conclusion

Diagram/Flowchart


--End of Paper 18—

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Reference in APA format	Maha M. Althobaiti, Amal Adnan Ashour, Nada A. Alhindi, Asim Althobaiti, Romany F. Mansour, Deepak Gupta, Ashish Khanna, "Deep Transfer Learning-Based Breast Cancer Detection and Classification Model Using Photoacoustic Multimodal Images", BioMed Research International, vol. 2022, Article ID 3714422, 13 pages, 2022. https://doi.org/10.1155/2022/3714422	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**

https://www.hindawi.com/journals/bmri/2022/3714422/	Maha M. Althobaiti, Amal Adnan Ashour, Nada A. Alhindi, Asim Althobaiti, Romany F. Mansour, Deepak Gupta,and Ashish Khanna	Biosynthesis, gold nanoparticles, living platelets, multimodal biomedical imaging, colloids, surfaces, and bio interfaces.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
Social Engineering Optimization with Deep Transfer Learning-Based Breast Cancer Detection and Classification Model Using Photoacoustic Multimodal Images	Aim is to detect and categorize the presence of breast cancer using ultrasound images.	Preprocessing using bilateral filtering, image segmentation using LEDNet model, feature extraction using ResNet-18 model, image classification using RNN and hyperparameter tuning using SEO algorithm.

The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process

The technique combines various image processing and deep learning techniques to detect and classify the presence of breast cancer using ultrasound images. It can accurately classify the presence of breast cancer but requires a large amount of data and computational resources.

	Process Steps	Advantage	Disadvantage (Limitation)
1	Pre-processing using bilateral filtering which smoothens the images without changing the edges.	It preserves the edges while smoothing the image.	It may not be effective in removing all types of noise.

2	Ground truth which involves labeling the images as benign, malignant, or normal.	It provides a reference for the classification model.	It requires manual labeling, which can be time-consuming and prone to errors.
3	Image segmentation using LEDNet model segments the breast region from the ultrasound image.	It reduces the complexity of the image and focuses on the region of interest.	It may not be effective in segmenting all types of breast tissue.
4	Feature extraction process using CNN-based ResNet-18 model from the segmented image using a deep learning model.	It can capture complex patterns and features that are difficult to detect manually.	It may require a large amount of data and computational resources.
5	Training images (BUSI dataset) which involves training the classification model using a dataset of ultrasound images.	It allows the model to learn from a large amount of data.	The dataset may not be representative of all types of breast tissue.
6	Image classification using recurrent neural network that classifies the ultrasound image as benign, malignant, or normal	It can accurately classify the presence of breast cancer.	It may require a large amount of data and computational resources.
7	Hyperparameter tuning using SEO algorithm that optimizes the hyperparameters of the classification model using a social engineering optimization algorithm.	It can improve the performance of the model.	It may require a large number of computational resources.
Major Impact Factors in this Work			

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The outcome variable indicating whether breast cancer is detected and classified using the proposed SEODTL-BDC model.	Biomedical Imaging Modalities: Magnetic Resonance Imaging (MRI), Ultrasonic Imaging, Optical Imaging: These are independent variables as they are the diverse imaging modalities employed in the study. Photoacoustic Multimodal Imaging (PAMI): This is a specific modality that combines optics and ultrasonic systems, considered an independent variable.	Biomedical Image Segmentation: LEDNet ModelActs as a moderating variable in the segmentation of biomedical images. Residual Network (ResNet-18): Acts as a moderating variable in extracting features from biomedical images.	Bilateral Filtering (BF)acts as a mediating variable in the image preprocessing stage, facilitating noise removal.

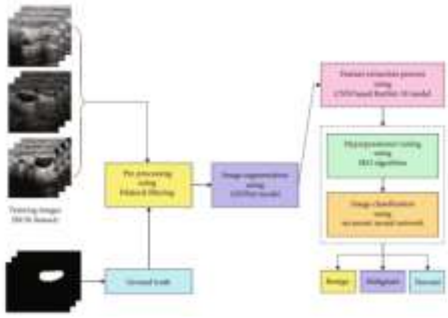
Relationship Among the Above 4 Variables in This article
The connection is found in the way that different biomedical imaging modalities are used to generate Photoacoustic Multimodal Imaging (PAMI). Under the direction of bilateral filtering and deep learning models, PAMI improves breast cancer detection and classification by combining various imaging data and enhancing image quality.

Input and Output	Feature of This Solution	Contribution & The Value of This Work

<table>
<tr>
<td><table><tr><th>Input</th><th>Output</th></tr><tr><td>Photoacoustic multimodal images of breast tissue</td><td>Classification of the input image as benign, malignant, or normal</td></tr></table></td>
<td>Developing a highly advanced and accurate solution for breast cancer detection and classification, which has the potential to significantly improve the diagnosis and treatment of breast cancer.</td>
<td>The development of a novel SEODTL-BDC model that achieves high accuracy in breast cancer detection and classification, while the value lies in its potential to improve breast cancer diagnosis and treatment through the use of deep transfer learning and multimodal imaging.</td>
</tr>
</table>

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
It’s potential to significantly improve breast cancer diagnosis and treatment, ultimately leading to better patient outcomes.	Challenges may arise in integrating the SEODTL-BDC model into existing healthcare systems and workflows, and concerns about false positives or false negatives in breast cancer diagnosis may need to be addressed.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
This work gives a promising approach to breast cancer detection and classification using advanced technologies. However, further research is needed to address the challenges of integrating this technology into clinical practice and to ensure that ethical considerations are adequately addressed.	TensorFlow, openCv,social engineering optimizer	1) Abstract 2) Introduction 3) Literature review 4) The proposed model 5) Results and discussions 6) Conclusion 7) References

Diagram/Flowchart


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Reference in APA format	Haribabu, M., & Guruviah, V. (2023). An Improved Multimodal Medical Image Fusion Approach Using Intuitionistic Fuzzy Set and Intuitionistic Fuzzy Cross-Correlation. *Diagnostics*, *13*(14), 2330. https://doi.org/10.3390/diagnostics13142330	
URL of the Reference	**Authors Names and Emails**	**Keywords in this Reference**
https://www.mdpi.com/2075-4418/13/14/2330	Maruturi Haribabu and Velmathi Guruvaiah	Medical imaging, image fusion, disease diagnosis, intuitionistic fuzzy set, intuitionistic fuzzy image, subjective and objective analysis.
The Name of the Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/ ... etc)	**The Goal (Objective) of this Solution & What is the problem that need to be solved**	**What are the components of it?**
An Improved Multimodal Medical Image Fusion Approach using Intuitionistic	Goal or objective: To propose an improved approach to multimodal medical image fusion using	The proposed solution uses Intuitionistic Fuzzy Set and Intuitionistic Fuzzy Cross-Correlation.

Fuzzy Set and Intuitionistic Fuzzy Cross-Correlation	intuitionistic fuzzy set and intuitionistic fuzzy cross-correlation. Problem: The need for better quality medical images that can aid in the diagnostic process.		
The Process (Mechanism) of this Work; Means How the Problem has Solved & Advantage & Disadvantage of Each Step in This Process			
	Process Steps	**Advantage**	**Disadvantage (Limitation)**
1	Fuzzification of registered input images	It helps to handle the uncertainty and imprecision in the input images.	may lead to a loss of information.
2	Creation of intuitionistic fuzzy images	It helps to enhance the intensity levels of the input images	may lead to a loss of spatial information.
3	Fusing the intuitionistic fuzzy images	It helps to obtain a single fused image with more complementary information and better quality.	may lead to a loss of some information during the fusion process.
4	Defuzzification of the final enhanced fused image	It helps to obtain a crisp image that can be easily interpreted by medical professionals.	may lead to a loss of some information during the defuzzification process
Major Impact Factors in this Work			

Dependent Variable	Independent Variable	Moderating variable	Mediating (Intervening) variable
The quality of the fused image obtained after the proposed IFS-MMIF method, assessed subjectively and objectively. .	Fuzzy Set-Based Multimodal Medical Image Fusion (IFS-MMIF) Approach: The primary intervention or treatment in this study is the suggested fusion method, which serves as the independent variable.	The choice of various medical image datasets for testing and evaluation moderates the relationship between the independent variable (IFS-MMIF) and the dependent variables, as different medical images may exhibit varied characteristics.	Calculating Intuitionistic Fuzzy Entropy variable influences the quality of the fused image by mediating the process of identifying the ideal membership, non-membership, and hesitation degrees within the Intuitionistic Fuzzy Set.

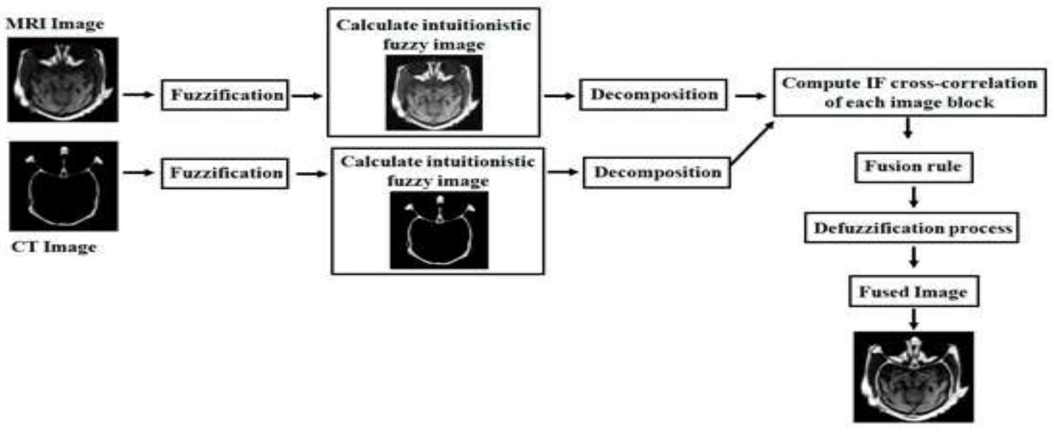
Relationship Among the Above 4 Variables in This article
The Intuitionistic Fuzzy Set-Based Multimodal Medical Image Fusion (IFS-MMIF) method, as the independent variable, influences enhanced fused image quality (dependent variable) through the mediating role of intuitionistic fuzzy entropy, with the choice of medical image datasets moderating the evaluation process.

Input and Output		Feature of This Solution	Contribution & The Value of This Work
Input	**Output**		
Medical images such as CT scans, MRI scans, related to lung cancer.	Generation of fused medical image	The proposed approach helps to obtain a single fused image with more complementary information and better quality compared to the individual input images.	The proposed approach uses intuitionistic fuzzy set and intuitionistic fuzzy cross-correlation to handle the uncertainty and imprecision in the input images. This can be valuable for medical professionals in dealing with

		the inherent uncertainty and imprecision in medical images.

Positive Impact of this Solution in This Project Domain	**Negative Impact of this Solution in This Project Domain**
The proposed approach can help medical professionals make more accurate diagnoses by providing a better quality fused image with more complementary information.	The solution has challenges which includes increased computational complexity and difficulty in interpretation.

Analyse This Work By Critical Thinking	**The Tools That Assessed this Work**	**What is the Structure of this Paper**
The proposed solution presents a well-researched and detailed approach to medical image fusion that has the potential to improve the accuracy of diagnoses and treatment decisions.	These tools include MATLAB, ImageJ, and SPSS.	1) Abstract 2) Introduction 3) Related Works 4) Materials and Methods 5) Proposed Fusion Method 6) Experimental Results and Discussion 7) Conclusions 8) References

Diagram/Flowchart


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2.2 COMPARISION TABLE:

Author	Year	Approach	Description
Zsoter N, Bandi P, Szabo G, Toth Z, Bundschuh R. A., Dinges J, Papp L.	2012	Lung affinity map generation, nodule detection, nodule classification.	An automated method for detecting lung nodules in PET-CT studies, significantly reducing localization time and proving effective in clinical evaluation for oncology practices.
Ch. Hima Bindu and Dr. K. Veera Swamy	2014	Automatic Segmentation Process, Feature-Level Fusion and Performance Evaluation Metrics	Feature-level image fusion method using content-based automatic segmentation, enhancing multimodal image information into a meaningful and informative fused image.
Himanshi, V. Bhateja, A. Krishn and A. Sahu	2014	Gray scale conversion, PCA, DTCWT decomposition, and image fusion	Decomposing the source images using DTCWT and applying PCA in the complex wavelet domain to fuse the images.
Z. Guo, X. Li, H. Huang, N. Guo and Q. Li	2018	Deep Convolutional Neural Network (CNN), Multi-Modality image processing and Fusion Techniques.	CNN-based segmentation system for soft tissue sarcoma detection from multi-modal medical images, investigating diverse fusion schemes for improved accuracy in biomedical imaging analysis.
M B Abdulkareem	2018	DWT and Inverse DWT	Preprocessing of images, decomposition using DWT, obtaining the fused image via Inverse DWT and postprocessing the image
K. Vanitha, D. Satyanarayana and M. N. G. Prasad	2019	Hybrid l1-l0 decomposition model, Weighted average fusion rule, Average	A hybrid L1-L0 decomposition-based two-scale fusion method for multimodal medical images, aiming to enhance information

		fusion rule, Linear combination and Objective criteria	preservation and produce superior fused images, assessed through objective criteria.
Jiaxin Li, Houjin Chen, Yanfeng Li and Yahui Peng	2019	Densely connected fully convolutional network and hyper-densely connected CNN model	Uses a deep learning approach to accurately segment lung tumors on multi-modal MR images.
K. S. Asish Reddy, K. Kalyan Kumar, K. N. Kumar, V. Bhavana and H. K. Krishnappa	2019	Discrete wavelet transforms (DWT), Principal Component Analysis (PCA)	An enhanced medical image fusion technique using DWT and PCA, aiming to improve brain tumor detection and other cancer diagnoses, offering more informative and accurate fused images for clinical diagnosis.
H Yan and Z. Li	2019	MFDF, Weight map and guide filtering	Performs one level image decomposition and generates a weight map to single fused image.
V. Amala Rani and S. Lalitha Kumari	2020	Empirical mode decomposition (EMD) and discrete wavelet transform (DWT).	A hybrid image fusion framework combining empirical mode decomposition and discrete wavelet transform for MRI and CT brain tumor images, aiming for enhanced functional and structural information preservation without image distortion.
Manjit Kaur and Dilbag Singh	2020	Multi-objective differential evolution algorithm and Inception model-based deep neural network that uses a non-subsampled contourlet transform	A novel technique using deep neural networks and multi-objective differential evolution for superior multi-modality medical image fusion, outperforming existing approaches.

Lifang Wang, Jin Zhang, Yang Liu, Jia Mi and Jiong Zhang	2021	Gabor representation, multi-CNNs and fuzzy neural networks	Multimodal medical image fusion technique based on Gabor representation combined with multi-CNN and fuzzy neural network, showcasing superior performance compared to state-of-the-art methods.
C. Gao, C. Song, Y. Zhang, D. Qi and Y. Yu	2021	Latent Low-Rank Representation, Rolling Guided Image Filtering, CNN based Fusion Rules, Improved Visual Saliency Mapping Image Filtering and Laplacian Pyramid Decomposition	An infrared and visible image fusion technique employing Latent Low-Rank Representation nested with Rolling Guided Image Filtering, demonstrating superior performance compared to existing methods.
X. Fu, L. Bi, A. Kumar, M. Fulham and J. Kim	2021	Multimodal spatial attention module and convolutional neural network backbone	A deep learning-based approach to learn about the features of the image and generate segmentation map which is refined by MSAM by emphasizing regions related to tumors and suppressing normal regions.
K. Kusram, S. Transue and M. -H. Choi	2021	Coarse Fusion Network (CFN), Refining Fusion Network (RFN), Nonlinear Image Registration, Depth-Thermal Fusion and Two-Phase CNN	AccuFusion, a two-phase CNN-based method for per-pixel multimodal image fusion, overcoming limitations in global alignment and significantly enhancing accuracy.
James Barrett and Thiago Viana	2022	Training Deep neural networks; extracted features and Evaluation	An EMM-LC Fusion model that leverages multimodal data fusion and intermediate feature extraction

		using various evaluation metrics such as sensitivity, specificity, accuracy, and F1 score.	via machine learning for improved lung cancer detection.
Y. Zhang, H. Zhang, L. Xiao, Y. Bai, V. D. Calhoun and Y. -P. Wang	2022	Hypergraph Representation, Inter- and Intra-Modality Relationships and HMF Algorithm	Hypergraph-based Multi-modal data Fusion (HMF) algorithm for integrating imaging and genetics data, enhancing schizophrenia classification accuracy by capturing complex interactions among risk genes, environmental factors, and abnormal brain regions.
Kaushik Pratim Das and Chandra J	2022	Multiple medical images, image registration techniques, image fusion algorithms, and image quality assessment methods	Efficient medical image fusion techniques, explores recent advancements, and assesses the impact of deep learning in automating the process for enhanced image quality and clinical information retention.
Maha M. Althobaiti, Amal Adnan Ashour, Nada A. Alhindi, Asim Althobaiti, Romany F. Mansour, Deepak Gupta and Ashish Khanna	2022	Preprocessing: bilateral filtering, LEDNet model for image segmentation,x Feature extraction: ResNet-18 model, Image classification: RNN and hyperparameter tuning with SEO algorithm	A highly advanced and accurate solution for breast cancer detection and classification, which has the potential to significantly improve the diagnosis and treatment of breast cancer.
Haribabu, M., and Guruviah, V	2023	Intuitionistic Fuzzy Set and Intuitionistic Fuzzy Cross-Correlation	An intuitionistic fuzzy set and intuitistic fuzzy cross-correlation to handle the

			uncertainty and imprecision in input images. This can be valuable for medical professionals in dealing with the inherent uncertainty and imprecision in medical images.

2.3 WORK EVALUATION TABLE:

	Work Goal	**System's Components**	**System's Mechanism**	**Features /Characteristics**	**Performance**	**Advantages**	**Limitations /Disadvantages**	**Results**
LIFANG WANG, JIN ZHANG, YANG LIU, JIAMI, AND JIONG ZHANG 2021	The goal of the proposed solution is to improve the quality of multi modal medical image fusion.	Author used Gabor representation, multi-CNNs and fuzzy neural networks for obtaining fused images.	The system uses Gabor representation, multi-CNN, and fuzzy neural network techniques to enhance the texture features and edge	The proposed solution outperforms nine recent states of the art multimodal fusion methods in terms of average mutual information, spatial frequenc	The proposed solution achieved better performance than other comparative fusion methods in objective evaluation and visual quality.	Integrates the rich texture features and clear edge information of different images into a single fused image, which improves the quality	The proposed solution has the disadvantage of increased computational complexity and longer training time.	The proposed solution outperforms methods by significantly enhancing objective evaluation and visual quality measures, achieving up to 13% improvement in mutual informatio

			information of the source images and generate a high-quality fused image.	y, standard deviation, and edge retention information.		of image fusion and assists doctors in disease diagnosis.		n, 20% in spatial frequency, 14.4% in standard deviation, and 43% in edge retention.
Ch. Hima Bindu, K. Veera Swamy	The goal of this solution is to achieve less complex fusion and improve the performance of image fusion methods compa	image fusion using a proposed region-based fusion method with evaluation based on Fusion Symmetry and Peak Signal	Proposed method focuses on region-based fusion, merging selected regions to reconstruct the final fused image. Evaluation of the method	the use of multi-modal image fusion, a novel conceptual image fusion architecture, the use of Convolutional Neural Networks (CNNs), and the evaluation of	The proposed image fusion method utilizes region-based feature level fusion, overcoming the drawbacks of pixel-level methods. It achieves better performa	it provides a unified framework for multi-modal image processing, which can guide the methodology design for various	it may not be suitable for all scenarios, and some modifications may be necessary.	The output is a generalized framework of image fusion for supervised learning in biomedical image

	red to existing methods.	to Noise Ratio.	includes metrics like fusion symmetry and peak signal-to-noise ratio (PSNR) for performance assessment.	performance differences across different fusion schemes. These features contribute to improved accuracy and robustness of medical image segmentation.	nce than existing methods, as evidenced by higher Fusion Symmetry and Peak Signal to Noise Ratio (PSNR) values. The method is visually and quantitatively evaluated with CT-MRI and MRI-PET images, demonstrating its effectiveness in medical diagnostics.	applications.		

Himanshi, Vikrant Bhateja, Abhinav Krishn and Akanksha Sahu	To present an improved fusion approach for medical images using PCA and DTCWT.	Gray scale conversion, DTCWT decomposition, PCA and image fusion	Decomposing the source images using DTCWT and applying PCA in the complex wavelet domain to fuse the images.	Shift invariance, high directionality, and feature enhancement properties	Reported to be satisfactory, with higher values of fusion metrics supporting the improvement in visual quality of the fused image.	Improved visual quality of fused images	Computational intensity of DTCWT, potentially increasing processing time and cost, and the risk of information loss during fusion	A fused image with higher fusion metric values
Z. Guo, X. Li, H. Huang, N. Guo and Q. Li	a generalized framework of image fusion for supervised learning to	a multi-modal convolutional neural network approach for medical image segmentation, which	Conceptual design for image fusion schemes, including fusing at feature level,	multi-modal image fusion, a novel conceptual image fusion architecture, the use of Convolutional	The paper proposes a generalized framework for image fusion in biomedical image analysis using	it provides a unified framework for multi-modal image processing, which can	it may not be suitable for all scenarios, and some modifications may be necessary.	The output is a generalized framework of image fusion for supervised learning in biomedical image.

	implement the fusion schemes based on deep CNN to improve the accuracy and robustness of medical image segmentation using multi-modal CNN.	includes three schemes for fusing information from different image modalities: fusing at feature level, fusing at classifier level, and fusing at decision level.	fusing at classifier level, and fusing at decision level.	Neural Networks (CNNs), and the evaluation of performance differences across different fusion schemes. These features contribute to improved accuracy and robustness of medical image segmentation.	deep convolutional neural networks. The fusion networks outperform single-modality counterparts on the TCIA Soft-tissue-Sarcoma dataset, demonstrating their potential for multi-modal medical image analysis.	guide the methodology design for various applications.		
Mohammed Basil Abdul	To enhance the quality of	DWT and Inverse DWT	Preprocessing of images, decomp	Preservation of both the spectral and	Achieves around 90-95% more accurate	Preservation of both the spectral and	May introduce some artifacts and	A fused image with accurate outcomes preserving

kareem	medical images for clinical diagnosis through image fusion technique		osition using DWT, obtaining the fused image via Inverse DWT and post-processing the image	anatomical data, and the ability to dilute the color change.	outcomes and preserves both the spectral and anatomical data	anatomical data and provides a multi-resolution representation	distortions in the processed images.	both spectral and anatomical data
K.Vanitha, Dr.D. Satyanarayana and Dr.M. N.Giri Prasad	To develop a new method for multi modal medical image fusion that can provide a more compl	Hybrid l1-l0 decomposition model, Weighted average fusion rule, Average fusion rule, Linear combination and Objecti	uses a l1-l0 decomposition model and weighted average fusion rule to combine detailed information, average fusion	Evaluation using objective criteria such as mean, standard deviation, and mutual information, which allows for a quantitative assessme	outperforms existing methods in terms of image quality and objective evaluation.	can provide a more complete and accurate representation of the underlying anatomy or pathology, even when source images	-	A fused image which helps researchers compare and benchmark different methods for medical image fusion, which can lead to further improveme

	ete and accurate representation of the underlying anatomy or pathology	ve criteria	rule for base layers, and a linear combination for the final fused image, evaluated with objective criteria for performance comparison.	nt of its performance.		have poor contrast		nts in the field.
Jiaxin Li, Houjin Chen, Yanfeng Li and Yahui Peng	To improve the accuracy of lung tumor segmentation on multi-modal MR	A densely connected fully convolutional network and a hyper-densely connected CNN model	Uses a deep learning approach to accurately segment lung tumors on multi-modal	Combining MR imaging modalities for anatomical and functional information, utilizing a novel	Efficient tumor segmentation and assessing performance with Dice Similarity Coefficient (DSC)	Segmenting lung tumors due to the complex and diverse appearance of tumors on	Practical application might be hindered in certain settings	Binary segmentation mask that identifies the tumor region in the images.

	images, which is important for the classification of tumors	for multi-modality fusion	MR images.	network architecture blending U-Net and densely connected CNN characteristics		different modalities.		
K SAI ASISh REDDY, K KALYAN KUMAR, K. NAVEEN KUMAR, BHAVANA. V, KRISHNA	To enhance the accuracy of clinical diagnosis through the fusion of multi modal medical images.	The components of the proposed solution include the use of Discrete wavelet transform (DWT), Principal Component Analysi	The extraction of fine details from the input images using DWT and PCA algorithms, followed by the fusion of the extracted details	This solution merges multiple medical images from PET, MRI, and CT into a single image, providing accurate, informative data for clinical	The proposed solution provides more accurate and informative medical images for clinical diagnosis, which can lead to better patient outcomes and	The advantages of this process include improved accuracy, reduced data, applicability to multiple modalities, and reliability	The limitations of this process include complexity, processing time, and sensitivity to input quality.	The results of this work show that the fusion process provides more accurate and informative images for clinical diagnosis, which can lead to better patient outcomes and

PPA H.K 2019		s (PCA) for image fusion.	into a single image using a fusion rule. The fused image is then post-processed to enhance its quality and remove any artifacts	diagnosis using advanced algorithms like DWT and PCA.	improved healthcare delivery.			improved healthcare delivery.
Huibin Yan and Zhongmin Li	to provide a fast and efficient solution for multi-modal medical image	MFDF, Weight map and guide filtering	performs one-level image decomposition and generates a weight map which is used to	High contrast, retain more edge and texture information	The fused images are more in line with human vision with high contxxxxxrast.	fast and efficient, and does not have the problem of selecting the number of decomp	Sometimes may not be able to preserve the edge and texture information of the	A fused image

	fusion in spatial domain.		single fused image.			osition levels.	input images.	
V. AMALA RANI AND S. LALITHA KUMARI 2020	Develop a hybrid image fusion technique that can effectively combine the MRI and CT images of brain to provide high quality fused images	The proposed hybrid image fusion algorithm consists of two main components: Empirical mode decomposition (EMD) and discrete wavelet transform (DWT).	The system decomposes input images using EMD to extract relevant features and then employs DWT-based fusion to combine these features, ensuring the retention of	The method focuses on preserving functional information while maintaining spatial characteristics from the original images without introducing any distortion in the final	The performance of the proposed method is claimed to demonstrate the dominance of the obtained fusion results.	The method claims to retain functional information, spatial characteristics, and produce distortion-free fused images, addressing storage issues and offering a hybrid fusion	The algorithm's effectiveness in medical imaging tasks depends on input image quality and task context, necessitating further research for validation across diverse datasets and	The fusion results obtained are observed and quantitatively analysed, indicating a favourable hybrid fusion response in combining MRI and CT images of the brain.

	with no distortion.		functional details and spatial characteristics without introducing distortion into the fused image.	fused image.		approach.	addressing complex computational steps and practical implementation challenges.	
Manjit Kaur Dilbag Singh 2020	The goal is to improve the accuracy and reliability of medical imaging for diagnosis and treatment of variou	it consists of a multi-objective differential evolution algorithm and an Xception model-based deep	It uses a multi-objective differential evolution algorithm to optimize the weights of an Xception model-based	The Xception model is a deep neural network that has been shown to perform well on image classification tasks. Additionally, we use a	_	The multi-objective differential evolution algorithm is a powerful optimization technique that can help to select	The choice of fusion functions may affect the performance of the overall approach and may require extensive	to fuse multi-modality medical images to obtain a more informative and accurate representation of the underlying anatomy or pathology.

	s medical conditions, leading to better patient outcomes and improved quality of life	neural network that uses a non-subsampled contourlet transform to decompose	deep neural network. It the decomposed subbands of the medical images obtained using a non-subsampled contourlet transform as input and produces a fused image	non-subsampled contourlet transform (NSCT) to decompose the input images into subbands.		the most informative features from the input images,to improve the accuracy and efficiency of the approach.	experimentation and validation.	
LIFANG WANG, JIN ZHANG, YAN	The goal of the proposed solution is to impro	Author used Gabor representation, multi-CNNs and	The system uses Gabor representation, multi-CNN,	The proposed solution outperforms nine recent states of the art	The proposed solution achieved better performance than other	Integrates the rich texture features and clear edge	The proposed solution has the disadvantage of increase	The proposed solution outperforms methods by significantly

G LIU, JIA MI, AND JIONG ZHANG 2021	ve the quality of multimodal medical image fusion.	fuzzy neural networks for obtaining fused images.	and fuzzy neural network techniques to enhance the texture features and edge information of the source images and generate a high-quality fused image.	multimodal fusion methods in terms of average mutual information, spatial frequency, standard deviation, and edge retention information.	comparative fusion methods in objective evaluation and visual quality.	information of different images into a single fused image, which improves the quality of image fusion and assists doctors in disease diagnosis.	d computational complexity and longer training time.	enhancing objective evaluation and visual quality measures, achieving up to 13% improvement in mutual information, 20% in spatial frequency, 14.4% in standard deviation, and 43% in edge retention.
C. Gao, C. Song, Y. Zhang, D. Qi	the performance of infrared and visible image fusion	The proposed method for infrared and visible image	the proposed method shows promising results in terms of preserving image	The proposed fusion method uses LatLRR with denoising and	The paper proposes a fusion method based on LatLRR nested with RGIF. It	It can effectively preserve texture detail information,	While the proposed method has many advantages,	The proposed method for infrared and visible image fusion is based on LatLRR

and Y. Yu	by using a novel metho d that combi nes LatLR R (Latent Low-Rank Repres entatio n) with RGIF (Recur sive Guide d Image Filteri ng). The solutio n aims to enhanc e image contra st, sharpn	fusion consists of five compon ents: image decomp osition, acquisit ion of a detail-enhance d layer, fusion of low-rank sublaye rs, fusion of saliency sublaye rs, and image reconstr uction. These compon ents work together to enhance	details, contrast , and overall structur al similarit y. Howeve r, there are still some areas where further improve ments can be made to address the limitati ons mention ed above.	local structure represent ation capabiliti es for image decompo sition, nested with RGIF for image enhance ment. It employs a two-level decompo sition and three-layer fusion approach , allowing for flexible fusion of infrared and	outperfor ms other methods in visual quality and objective evaluatio n metrics. The fused images exhibit high sharpness and effectivel y preserve important informati on.	resultin g in sharper and more distinct features in the fused image. It also provide s high contrast and good overall structur al similarit y between the fused image and the source image. Additio nally, the propose d	there are also some limitati ons. In certain cases, such as the fusion of images with tree canopie s or figures, artifacts may appear on the edges of the contour s. The fused images may also have less contrast informa	nested with RGIF. It involves a two-level decomposit ion and three-layer fusion approach. The method utilizes LatLRR for image decomposit ion and RGIF for image enhanceme nt. It also incorporate s convolutio nal neural network (CNN) based fusion rules for detail layer fusion and adaptive weighting

	ess, and richness of detailed information, providing better fusion results compared to other methods.	image contrast, sharpness, and richness of detailed information.		visible images.		method can preserve rich and effective information, making it suitable for various types of image processing tasks.	tion compared to other methods. Additionally, the sky background of the fused image may appear dark, affecting the acquisition of information.	of regional energy features for saliency sublayer fusion.

XIAOHANG FU, LEI BI, ASHNIL KUMAR, MICHEAL FULHAM, AND JINMAN KIM 2021	To improve the accuracy of tumor segmentation in PET-CT images using a deep-learning based frame work with a multi modal special attention module.	The proposed deep learning framework uses a multimodal spatial attention module and a convolutional neural network backbone to segment PET-CT images, focusing on tumor-related regions.	A deep learning-based approach is used to learn the features of the image and generate segmentation map which is refined by MSAM by emphasizing regions related to tumors and suppressing normal regions.	The proposed solution uses PET and CT modalities for improved tumor segmentation accuracy. It can handle varied anatomical and functional features. The framework outperforms state-of-the-art methods in segmentation accuracy	The proposed framework outperforms state-of-the-art methods in terms of segmentation accuracy, as measured by the Dice similarity coefficient (DSC).	Improves the accuracy and reliability of tumor segmentation in PET-CT images, doesn't require tumor boundaries / initialization seeds to be pre-defined, and can handle more varied, challenging anatomical and functional features	The proposed framework can be computationally expensive and may require a large amount of training data to achieve optimal performance.	The results demonstrate that the proposed framework outperforms state-of-the-art methods in terms of segmentation accuracy, as measured by the Dice similarity coefficient (DSC).

K. Kusram, S. Transue and M. - H. Choi	method for fusing multiple imaging modalities at a per-pixel level, resulting in an efficient and accurate image registration. By employing a two-phase non-linear registration method, they	The components include a hypergraph-based manifold regularization, a multi-modal feature selection method, and a multi-task multi-linear regression model for predicting cognitive scores. It also	The proposed method assumes the provision of depth and thermal images that are synchronized for training. Image-space transformations are used to generate training data for the CFN and RFN.	the feature of this solution is its ability to fuse multiple imaging modalities at a per-pixel level using a two-phase non-linear registration method, resulting in an efficient and accurate image registration.	RFN approach improves edge accuracy by 18% over traditional methods, showcasing enhanced alignment in diverse scenarios. AccuFusion method and efficient system configuration enable real-time multimodal fusion on GPU, promising precise alignment for various	It reduces the computational complexity of the registration process.	it may not be able to handle non-linear deformations.	The output of the paper is a fused image that combines multiple imaging modalities at a per-pixel level, resulting in an efficient and accurate image registration. The authors achieve this by developing a two-phase non-linear registration method using convolutional neural networks.

	achieve an increase of 18% in average accuracy over global registration.	involves integrating SNP, DNA methylation, and fMRI data to improve classification accuracy and biomarker detection.			applications.			
Barrett, J., & Viana, T. (2022)	Enhanced lung cancer classification using multi modal fusion	Training of deep neural networks using extracted features. Evaluation on evaluati	_	The use of a multimodal fusion approach that combines information from multiple modalities,	_	Ability to combine complementary information from different modalities and improve	Potential loss of information and the need for careful selection of parameters.	classification of lung cancer

		on of the trained model using various evaluation metrics such as sensitivity, specificity, accuracy, and F1 score.		including CT scans and clinical data, to improve the accuracy of lung cancer detection.		the accuracy of the model.		
Y. Zhang, H. Zhang	develop a novel algorithm called HMF that combines information from diverse	The HMF model for multi-modal data fusion using hypergraph-based manifold	The system utilizes hypergraph-based manifold regularization to incorporate subject relation	HMF that combines information from diverse sources for improved accuracy in diagnosing	The proposed Hypergraph-Based Manifold Regularization algorithm demonstrates superior performance in classifying	it can incorporate both structural information and complex interactions among subjects, which	it may require more computational resources and time.	The output is the validate their approach on both synthetic data and real samples from a schizophrenia study and show that HMF

	sources for improved accuracy in diagnosing complex brain disorders.	regularization.	ships for multi-modal joint learning. It optimizes the objective function iteratively, updating the weight vector based on subject similarities within and across modalities and terminates when the relative error is	complex brain disorders.	schizophrenia and identifying significant biomarkers compared to other models. By integrating multi-modal data and incorporating high-order relationships, the algorithm overcomes overfitting in high-dimensional data analysis.	can circumvent the overfitting problem in high dimension but low sample data.		outperforms several competing methods.

			satisfied.					
Das, K. P., & Chandra, J.	the goal of medical image fusion is to combine multiple medical images to produce a single image that contains more comprehensive and accurate information.	multiple medical images, image registration techniques, image fusion algorithms, and image quality assessment methods.	_	Comprehensive coverage of medical image fusion techniques for lung cancer diagnosis, including recent advances and the impact of deep learning techniques.	_	Improved accuracy of diagnosis is due to precise spatial alignment.	Need for computationally intensive algorithms	genertaes combined medical image

Maha M. Althobaiti, Amal Adnan Ashour, Nada A. Alhindi, Asim Althobaiti, Romany F. Mansour, Deepak Gupta, Ashish Khanna,	Aim is to detect and categorize the presence of breast cancer using ultrasound images	Preprocessing using bilateral filtering, image segmentation using LEDNet model, feature extraction using ResNet-18 model, image classification using RNN and hyperparameter tuning using SEO algorithm.	Developing a highly advanced and accurate solution for breast cancer detection and classification, which has the potential to significantly improve the diagnosis and treatment of breast cancer. .	_	It can capture complex patterns and features that are difficult to detect manually.	Need for computationally intensive algorithms.	_	detect and categorized the presence of cancer

Maruturi Haribabu and Velmathi Guruvaiah 2023	The goal is to propose an improved approach to multimodal medical image fusion using intuitionistic fuzzy set and intuitionistic fuzzy cross-correlation.	The proposed solution uses Intuitionistic Fuzzy Set and Intuitionistic Fuzzy Cross-Correlation.	It uses intuitionistic fuzzy set and fuzzy cross-correlation to handle the uncertainty and imprecision in the input images for medical professionals in dealing with the inherent uncertainty and imprecision in medical images.	The proposed approach helps to obtain a single fused image with more complementary information and better quality compared to the individual input images.	It helps to obtain a single fused image with more complementary information and better quality.	may lead to a loss of information.	-	Provides multimodal medical image

CHAPTER 3

PROPOSED SYSTEM

3.1 PROPOSED SYSTEM

The primary objective of the proposed system is to revolutionize the diagnostic process for brain tumors by integrating multimodal medical imaging data and leveraging advanced computational techniques. At its core, the system seeks to enhance the diagnostic capabilities by fusing MRI and CT images of the brain to generate a comprehensive and detailed representation of brain anatomy and pathology. By automating processes such as image registration, fusion, and tumor classification, the system aims to streamline the diagnostic workflow, providing clinicians with timely and accurate results.

3.2 OBJECTIVES OF PROPOSED SYSTEM

The objectives of the proposed system include the following:

- Implement a reliable image registration technique, such as Procrustes analysis, to align MRI and CT images accurately.

- Appling wavelet transforms to the registered images, decomposing them into sub-bands for further processing.

- Develop an effective image fusion algorithm that combines information from the different sub-bands, producing a high-quality fused image.

- Designing an intuitive user interface for inputting medical images, displaying the fused image, and interacting with the system.

- Implement a robust tumor identification mechanism using the CNN model, providing accurate results for further analysis.

3.3 ADVANTAGES OF PROPOSED SYSTEM

The proposed system has the following advantages:

- Combination of MRI and CT images improves image quality, providing a clearer view of the brain.
- Procrustes analysis ensures accurate alignment of images, reducing errors.
- Wavelet transforms capture diverse features from both modalities, improving representation.
- Separate fusion of different frequency components enhances feature preservation.
- Integrated CNN accurately identifies tumor types like glioma, meningioma, or pituitary tumors.
- Fused images and tumor type predictions provide comprehensive diagnostic support.
- Automated processes save time for medical professionals, enabling quicker decision-making.
- Non-invasive imaging reduces the need for invasive procedures like biopsies.
- Early detection and precise diagnosis lead to better patient outcomes.
- High-quality images and accurate classifications support research into brain tumors, leading to treatment advancements.

3.4 SYSTEM REQUIREMENTS

The system requirements for the development and deployment of the project as an application are specified in this section. These requirements are not be confused with the end-user system requirements.

S.NO	Requirements	Requirement type	Explanation
1.	Python	Programming language	Used to write the code and run.
2.	Visual Studio Code	Development Environment	Environment to write and execute the code.

3.	Wavelet Transforms	Used for fusion process	Wavelet transforms is used to capture and fuse components.
4.	Convolutional Neural Network	Used for classification	The CNN model is trained to classify tumors into specific types

Table 3.4.1 Requirements for developing and deploying the application.

3.4.1 SOFTWARE REQUIREMENTS

Below are the software requirements for application development:

- Operating System : Windows, MacOS, or Linux distributions.
- Programming Language : Python for implementing image processing and deep learning models.
- Development Environment : PyCharm, Visual Studio Code, or Jupyter Notebook.
- Libraries : OpenCV, Numpy, TensorFlow or PyTorch, tensorFlow, Scikit-learn, Matplotlib.

3.4.2 HARDWARE REQUIREMENTS

Below are the hardware requirements for the application development:

- Processor : intel i3(minimum)
- Ram : 4 GB (minimum)
- Hard Disk : 250GB (minimum)
- Input Devices : Keyboard and mouse.

3.4.3 FUNCTIONAL REQUIREMENTS

1. Input: The system should accept MRI and corresponding CT images of the brain as input.
2. Image Registration: Implement Procrustes analysis to align MRI and CT images based on selected coordinates.
3. Image Fusion: Utilize wavelet transforms to decompose registered images into sub-bands (LL, LH, HL, HH) for fusion.
4. Tumor Classification: Develop a trained CNN model capable of identifying the type of tumor (glioma, meningioma, pituitary) from the fused MRI and CT images.
5. Output: Display the fused image as the output of the fusion process, along with the predicted tumor type by the CNN model.

3.4.4 NON-FUNCTIONAL REQUIREMENTS

1. Reliability:
   a. The system should be reliable, producing consistent results in tumor classification across multiple executions.
   b. It should handle errors gracefully and provide informative error messages to users.
2. Security:
   a. The system should ensure the confidentiality and integrity of patient data throughout processing.
   b. It should implement appropriate access controls to prevent unauthorized access to sensitive information.
3. Accuracy:
   a. The image registration and fusion processes should be accurate to ensure reliable tumor classification.
   b. The CNN model should achieve high accuracy in tumor classification, minimizing misclassification errors.

3.5 IMPLEMENTATION TECHNOLOGIES

3.5.1 PROCRUSTES ANALYSIS:

Shape correspondence is an important aspect of imaging. Understanding shape is the basis of any correspondence. The correspondence and analysis of shapes plays a vital role, not only in determining correspondence, but also determining the validity of the algorithms used to place the landmarks in accurate locations. The analysis should be well defined so that it is unbiased and thorough in its evaluation. Procrustes analysis is a rigid shape analysis that uses isomorphic scaling, translation, and rotation to find the "best" fit between two or more landmarked shapes.

Procrustes analysis has many variations and forms. Of these forms, the generalized orthogonal Procrustes analysis is the most useful in shape correspondence, because of the orthogonal nature of the rotation matrix. Gower played an important role in the introduction and derivation of the generalized orthogonal Procrustes analysis in 1971-75. Though Hurley and Cattell first used the term Procrustes analysis in 1962 with a method that did not limit the transformation to an orthogonal matrix.

Shape and landmarks:

Shape and landmarks are two important concepts involved with generalized orthogonal Procrustes analysis. Both shape and landmarks have their own role in the process of aligning shapes. The following is an overview of shape and landmarks to give a foundation for the generalized orthogonal Procrustes analysis.

Shape: "All the geometrical information that remains when location, scale and rotational effects are filtered out from an object." By this definition of shape, there exists transforms that allow the shape to move so that the differences may be removed between two shapes while preserving the angles and parallel lines, and therefore preserving the shape itself. Isomorphic scaling, translation, and rotation are the three transforms used to align shapes. These shape-preserving transforms are called Euclidean similarity transforms.

Landmarks: Shape can be described as a finite number of points along the outline of the shape. These points are called landmarks.

There consists of three types of landmarks:

- Anatomical landmarks: expert (i.e. Doctor) assigned points that represent a biological object or objects.

- Mathematical landmarks: points assigned by some mathematical property (i.e. high curvature).
- Pseudo-landmarks: point located between the other two types of landmarks or points around the outline.

Generalized Orthogonal Procrustes Analysis: Procrustes analysis is the comparison of two sets of configurations (shapes). Therefore, Procrustes analysis is limited in its application. Generalized orthogonal Procrustes analysis (GPA) is the evaluation of k sets of configurations. With GPA the k sets can be aligned to one target shape or aligned to each other. This paper will discuss the latter, since it is easily adapted to one target shape.

Algorithm for generalized orthogonal Procrustes analysis:

1. Select one shape to be the approximate mean shape (i.e. the first shape in the set).
2. Align the shapes to the approximate mean shape.
    a. Calculate the centroid of each shape (or set of landmarks).
    b. Align all shapes centroid to the origin.
    c. Normalize each shapes centroid size.
    d. Rotate each shape to align with the newest approximate mean.
3. Calculate the new approximate mean from the aligned shapes.
4. If the approximate mean from steps 2 and 3 are different the return to step 2, otherwise you have found the true mean shape of the set

3.5.2 WAVELET TRANSFORMS:

Wavelet transforms are mathematical tools for analysing data where features vary over different scales. For signals, features can be frequencies varying over time, transients, or slowly varying trends. For images, features include edges and textures. Wavelet transforms were primarily created to address limitations of the Fourier transform. While Fourier analysis consists of decomposing a signal into sine waves of specific frequencies, wavelet analysis is based on decomposing signals into shifted and scaled versions of a wavelet. A wavelet, unlike a sine wave, is a rapidly decaying, wave-like oscillation. This enables wavelets to represent data across multiple scales. Different wavelets can be used depending on the application.

Audio signals, time-series financial data, and biomedical signals typically exhibit piecewise smooth behaviour punctuated by transients. Similarly, images typically include homogenous, piecewise smooth regions separated by transients, which appear as edges. For both signals and images, the smooth regions and transients can be sparsely represented with wavelet transforms.

Wavelet transforms can be classified into two broad classes:

- Continuous wavelet transforms (CWT)
- Discrete wavelet transforms (DWT).

Continuous wavelet transforms (CWT):

The continuous wavelet transform is a time-frequency transform, which is ideal for analysis of non-stationary signals. A signal being nonstationary means that its frequency-domain representation changes over time. CWT is similar to the short-time Fourier transform (STFT). The STFT uses a fixed window to create a local frequency analysis, while CWT tiles the time-frequency plane with variable-sized windows. The window widens in time, making it suitable for low-frequency phenomena, and narrows for high-frequency phenomena. The continuous wavelet transform can be used to analyse transient behaviour, rapidly changing frequencies, and slowly varying behaviour.

Discrete wavelet transforms (DWT):

Any wavelet transforms involving a discrete sampling of wavelets is called a DWT. It records location and frequency information. Among image fusion techniques, the method based on Discrete Wavelet Transform (DWT) is straightforward. The first step is multilayer decomposition of the source images, where the frequency content is used to separate the images into upper and lower sub-bands after which the pixels with the highest wavelet coefficients are selected for further processing. By converting the image from the spatial domain to the frequency domain, the DWT can recover the relevant frequency information. This approach allows flexibility in the fusion process to vary the fusion operator at different decom-position levels. In this project initially MRI and CT images are preprocessed to ensure concordance and homogeneity. Images are then decomposed into multiple frequency bands or scales using the DWT algorithm to extract relevant features of tumor morphology, size, and location and these decomposed coefficients from both methods are then subjected to fusion, where fusion rules are used to combine information efficiently. Different techniques such as averaging or maximum selection can be used, depending on the specific application. Fused multipliers reduce noise to increase the signal-to-noise ratio of the final image, resulting in optimal quality. Once the fusion is completed, the inverse DWT algorithm reconstructs the fused image in the spatial domain, combining the relevant features of the MRI and CT scans.

With the discrete wavelet transform scales are discretized more coarsely than with CWT. This makes DWT useful for compressing and denoising signals and images while preserving important features. You can use discrete wavelet transforms to perform multiresolution analysis and split signals into physically meaningful and interpretable components.

3.5.3 CONVOLUTIONAL NEURAL NETWORKS (CNN):

A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer Vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data. When it comes to Machine Learning, Artificial Neural Networks perform really well. Neural Networks are used in various datasets like images, audio, and text. Different types of Neural Networks are used for different purposes, for example for predicting the sequence of words we use Recurrent Neural Networks more precisely an LSTM, similarly for image classification we use Convolution Neural networks. In this blog, we are going to build a basic building block for CNN. Convolutional Neural Network (CNN) is the extended version of artificial neural networks (ANN) which is predominantly used to extract the feature from the grid-like matrix dataset. For example: visual datasets like images or videos where data patterns play an extensive role.

CNN architecture

Convolutional Neural Network consists of multiple layers like the input layer, Convolutional layer, Pooling layer, and fully connected layers.

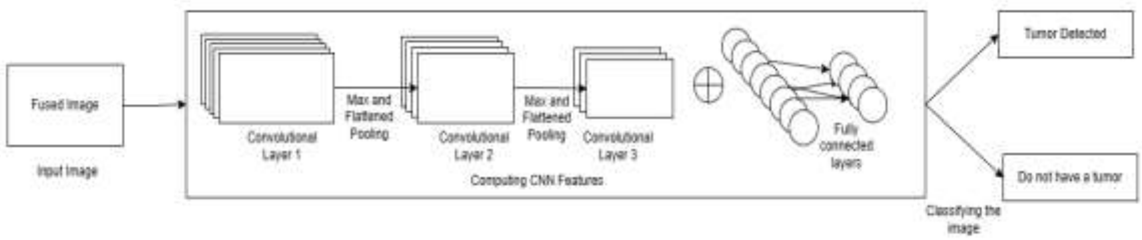

Figure 1: CNN Architecture

The Convolutional layer applies filters to the input image to extract features, the Pooling layer downsamples the image to reduce computation, and the fully connected layer makes the final prediction. The network learns the optimal filters through backpropagation and gradient descent.

How Convolutional Layers works

Convolution Neural Networks or covnets are neural networks that share their parameters. Imagine you have an image. It can be represented as a cuboid having its length, width and height.

Now imagine taking a small patch of this image and running a small neural network, called a filter or kernel on it, with say, K outputs and representing them vertically. Now slide that neural network across the whole image, as a result, we will get another image with different widths, heights, and depths. Instead of just R, G, and B channels now we have more channels but lesser width and height. This operation is called **Convolution**. If the patch size is the same as that of the image it will be a regular neural network. Because of this small patch, we have fewer weights.

Now let's talk about a bit of mathematics that is involved in the whole convolution process.

- Convolution layers consist of a set of learnable filters (or kernels) having small widths and heights and the same depth as that of input volume (3 if the input layer is image input).

- During the forward pass, we slide each filter across the whole input volume step by step where each step is called stride (which can have a value of 2, 3, or even 4 for high-dimensional images) and compute the dot product between the kernel weights and patch from input volume.

- As we slide our filters, we'll get a 2-D output for each filter and we'll stack them together as a result, we'll get output volume having a depth equal to the number of filters. The network will learn all the filters.

Layers used to build ConvNets

A complete Convolution Neural Networks architecture is also known as covnets. A covnets is a sequence of layers, and every layer transforms one volume to another through a differentiable function.

Types of layers:

Let's take an example by running a covnets on of image of dimension 32 x 32 x 3.

- **Input Layers:** It's the layer in which we give input to our model. In CNN, Generally, the input will be an image or a sequence of images. This layer holds the raw input of the image with width 32, height 32, and depth 3.

- **Convolutional Layers:** This is the layer, which is used to extract the feature from the input dataset. It applies a set of learnable filters known as the kernels to the input images. The filters/kernels are smaller matrices. it slides over the input image data and computes the dot product between kernel weight and the corresponding input image patch. The output of this layer is referred as feature maps.

- **Activation Layer:** By adding an activation function to the output of the preceding layer, activation layers add nonlinearity to the network. it will apply an element-wise activation function to the output of the convolution layer. Some common activation functions are **RELU**: max (0, x), **Tanh**, **Leaky RELU**, etc. The volume remains unchanged hence output volume will have dimensions 32 x 32 x 12.

- **Pooling Layer:** This layer is periodically inserted in the covnets and its main function is to reduce the size of volume which makes the computation fast reduces memory and also prevents overfitting. Two common types of pooling layers are **max pooling** and **average pooling**. If we use a max pool with 2 x 2 filters and stride 2, the resultant volume will be of dimension 16x16x12.

- **Flattening:** The resulting feature maps are flattened into a one-dimensional vector after the convolution and pooling layers so they can be passed into a completely linked layer for categorization or regression.x

- **Fully Connected Layers:** It takes the input from the previous layer and computes the final classification or regression task.
- **Output Layer:** The output from the fully connected layers is then fed into a logistic function for classification tasks like sigmoid or softmax which converts the output of each class into the probability score of each class.

CHAPTER 4

SYSTEM DESIGN

4.1 PROPOSED SYSTEM ARCHITECTURE

The proposed system encompasses the development of a specialized Flask-based web application tailored for multimodal medical image fusion.

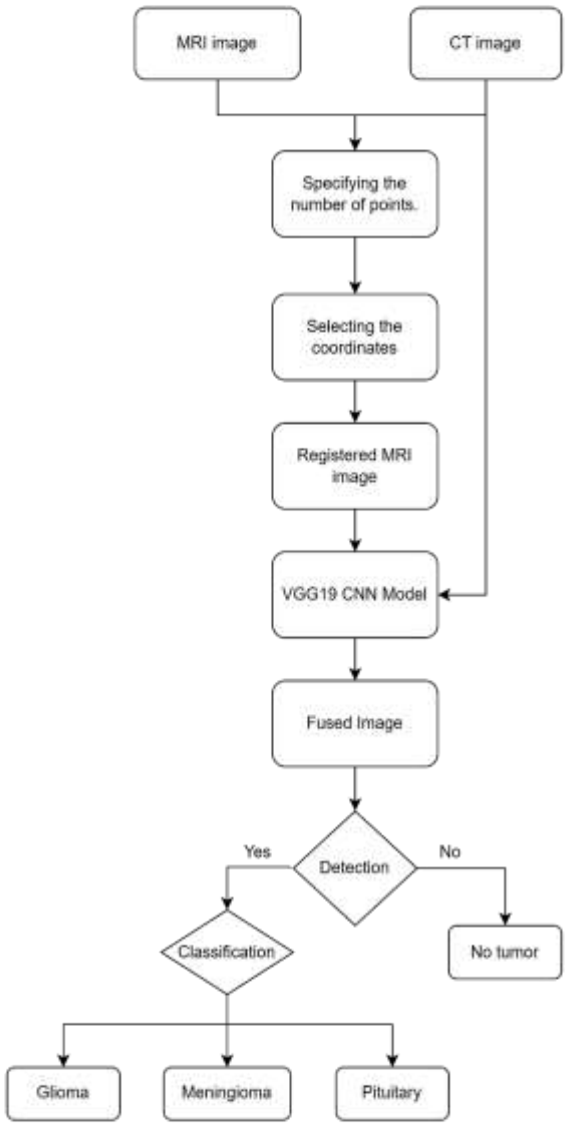

Figure 2: Proposed Architecture

4.2 APPLICATION MODULES

On The application on an overall involves Three main modules, which cater to the three main functions of this application, i.e., to generate Registered image, provide fused image and to Classify tumor.

4.2.1 Image Registration Module

The process of Image registration plays a pivotal function in clinical imaging, particularly while integrating pictures from one-of-a-kind modalities or received at one-of-a-kind times. This work focuses on the crucial project of registering brain MRI (Magnetic Resonance Imaging) and CT (Computed Tomography) scans, aiming to as it should be aligning these pics for comprehensive evaluation and prognosis. The registration method starts by means of identifying and extracting key anatomical functions or landmarks from both MRI and CT scans. These landmarks' function points of coherence, enabling the system to set up correspondences among the snap shots. The extracted landmarks are prepared into a matrix structure, where every row represents a landmark, and every column denotes coordinates in distinct dimensions (e.g., x, y, z). To ensure translational invariance for the duration of registration, the suggest is extracted from every measurement, and the matrix is targeted. This normalization step ensures that the registration procedure focuses entirely on modifications to variables and scales, enhancing the accuracy of the alignment. Procrustes analysis is then hired to compute the foremost transformation that minimizes the disparity between corresponding landmarks within the MRI and CT pics. This transformation encompasses adjustments in translation, rotation, and scaling to reap the first-rate feasible alignment. The Procrustes set of rules iteratively refines the transformation parameters until the alignment standards are glad, effectively minimizing the overall discrepancy between corresponding landmarks and ensuring a sturdy match among the 2 pictures. Once the greatest transformation is decided, it is carried out to a new set of landmarks to align a new configuration of pics. This registration system lays the muse for next fusion techniques, enabling the seamless integration of multimodal scientific snap shots and facilitating improved visualization, diagnostic accuracy, and medical decision-making within the medical domain. Through meticulous landmark-primarily based registration, this device empowers healthcare specialists with the equipment to correctly examine and interpret complex medical pix, in the end enhancing affected person care and outcomes.

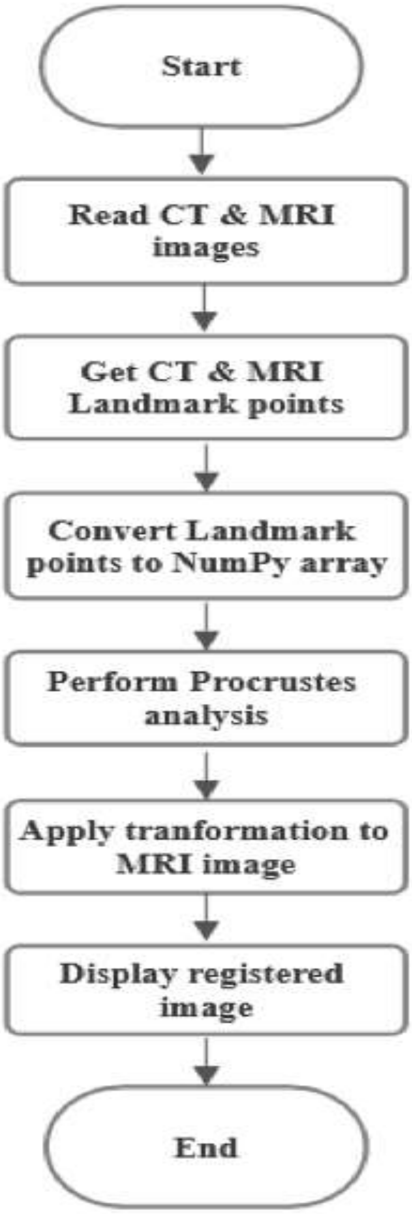

Figure 3: Workflow of Image Registration process

4.2.2 Image Fusion Module

The system commences with the MRI and CT photographs that have gone through registration, making sure spatial alignment and correct insurance of corresponding anatomical functions. This fusion system involves amalgamating categorized MRI and CT pictures, maintaining the maximum applicable functions from every modality. To gain this, the discrete wavelet transform (DWT) technique is hired for photo fusion. During DWT, registered MRI and CT pictures are decomposed into a couple of frequency bands, ensuing in 4 subbands: LL (low-low), LH (low-high), HL (excessive-low), and HH (high-high), every containing unique frequency information. From those subbands, the LL sub-band, representing lower structural records, and the HH sub-band, containing higher transcriptional information, are selected from each MRI and CT pics. These subbands are deemed extra suitable for brain anatomy depiction. Subsequently, the selected LL and HH sub-bands from the registered MRI and CT photographs are blended to form a fused image. This fusion procedure integrates low-degree structural information with repetitive transcriptional functions from each modality, making sure a complete illustration of brain anatomy. Furthermore, to enhance the fused image and extract problematic functions, the VGG19 version, a deep convolutional neural network (CNN), is integrated. VGG19 is gifted in recognizing photo sequences and discerning objects, as a result facilitating the extraction of great and meaningful capabilities from the fused pix. This permits precise anatomical imaging of the brain across MRI and CT modalities. The output of the picture fusion module is a composite image that offers a complete and informative depiction of brain anatomy. This fused photo serves as a valuable enter for subsequent diagnostic duties, which includes tumor detection and category, improving the accuracy and effectiveness of diagnostic techniques in clinical imaging.

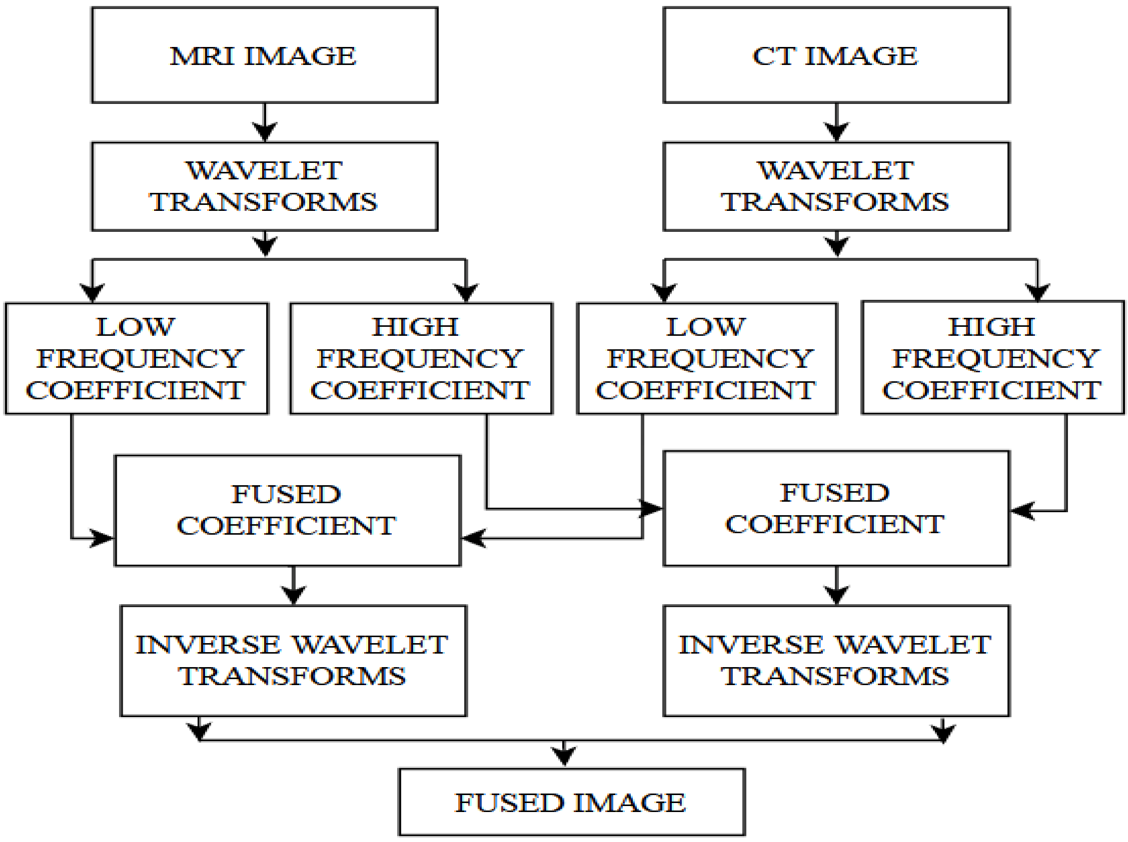

Figure 4: Workflow of Image Fusion

4.2.3 Image Classification Module

Following the Image fusion procedure, the module capitalizes at the fused picture to engage superior class techniques geared toward discerning and categorizing capability tumors within the Brain. Beginning with preprocessing steps to optimize the data, the fused image is then inputted into a convolutional neural network (CNN) architecture explicitly tailor-made for scientific photo analysis. This CNN structure, meticulously crafted and best-tuned for the intricacies of medical imaging, undergoes schooling on a meticulously curated and classified dataset comprising various times of mind tumors. As the fused Image propagates through the layers of the CNN, the community leverages it’s found-out features and styles to carry out an exhaustive evaluation. Each layer of the CNN extracts increasingly more summary representations, discerning complex details and diffused variations within the photo. Through the convolutional and pooling layers, the network correctly captures spatial hierarchies and invariant capabilities vital for tumor detection and classification. Trained on complete datasets encompassing diverse tumor types and anatomical variations, the CNN's type prowess extends beyond mere identity to unique categorization. The community distinguishes among distinctive tumor sorts, delineating between gliomas, meningiomas, and pituitary tumors with outstanding accuracy. This nuanced type enables clinicians to now not simplest pick out the presence of tumors but additionally to apprehend their particular nature and traits, important for devising tailored remedy techniques and prognostic checks.

4.3 UML Diagrams

UML stands for Unified Modelling Language. UML is a standardized fashionable-cause modelling language in the subject of object-oriented software engineering. In its modern shape, UML comprises of two essential components: a Meta-model and a notation. The Unified Modelling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software program machine, in addition to for commercial enterprise modelling and other non-software systems. The UML uses more often than not graphical notations to express the design of software program projects.

4.3.1 Use Case Diagram

In the Unified Modeling Language (UML), a use case diagram is a behavioral diagram that stems from use-case analysis. Its number one objective is to provide a visual summary of a gadget's capability, showcasing actors, their objectives (portrayed as use cases), and any relationships amongst those use cases. The fundamental aim of a use case diagram is to demonstrate which device capabilities are accomplished for each actor worried, while additionally illustrating the jobs played via these actors within the gadget.

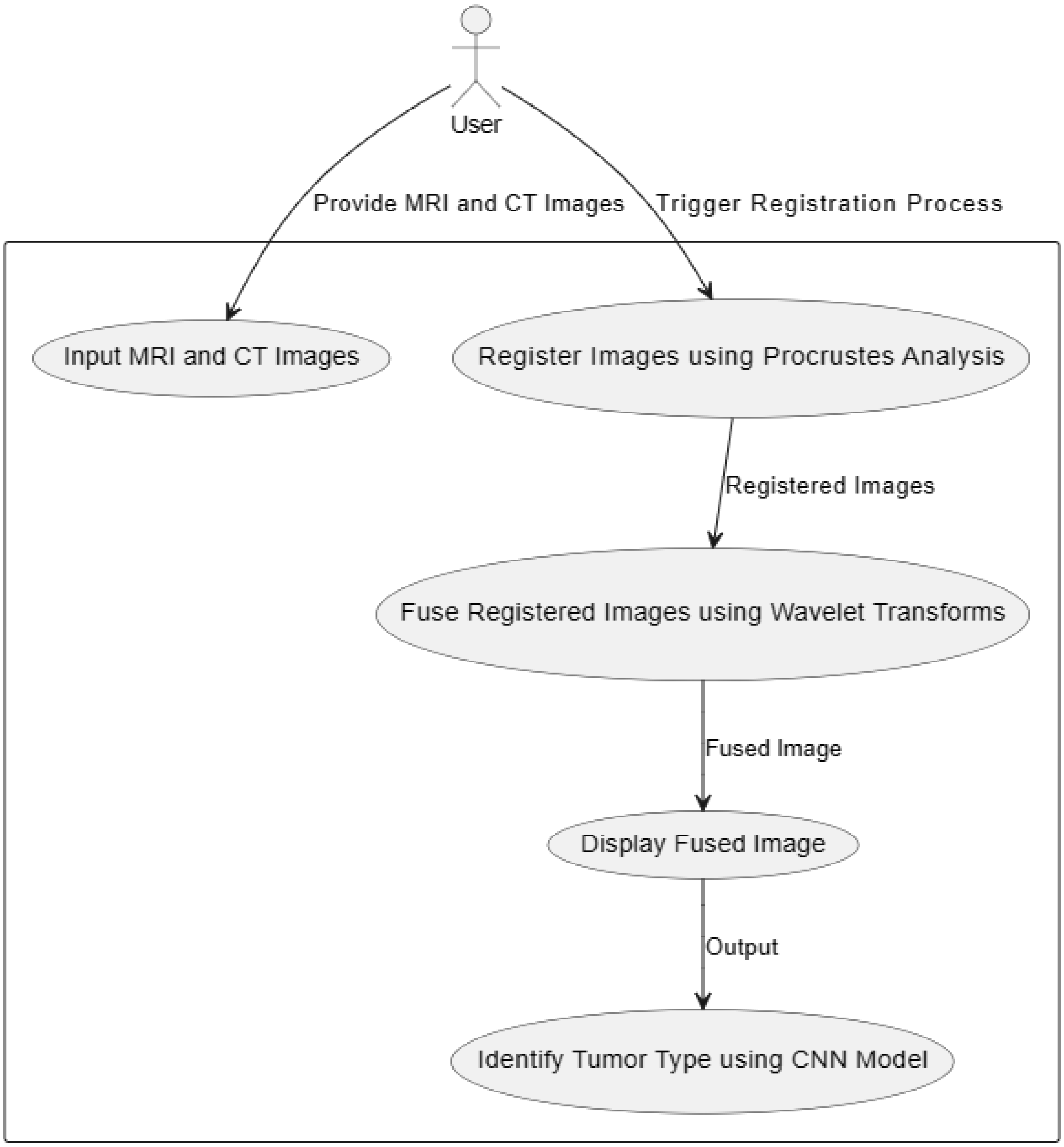

Figure 5: Use case Diagram

4.3.2 Class Diagram

In software engineering, a class diagram within the Unified Modeling Language (UML) is a static shape diagram that delineates the architecture of a machine. It achieves this by using illustrating the training within the gadget, inclusive of their attributes, operations (or techniques), and the connections between those classes. This diagram elucidates the distribution of statistics among lessons and clarifies which elegance is responsible for housing unique records.

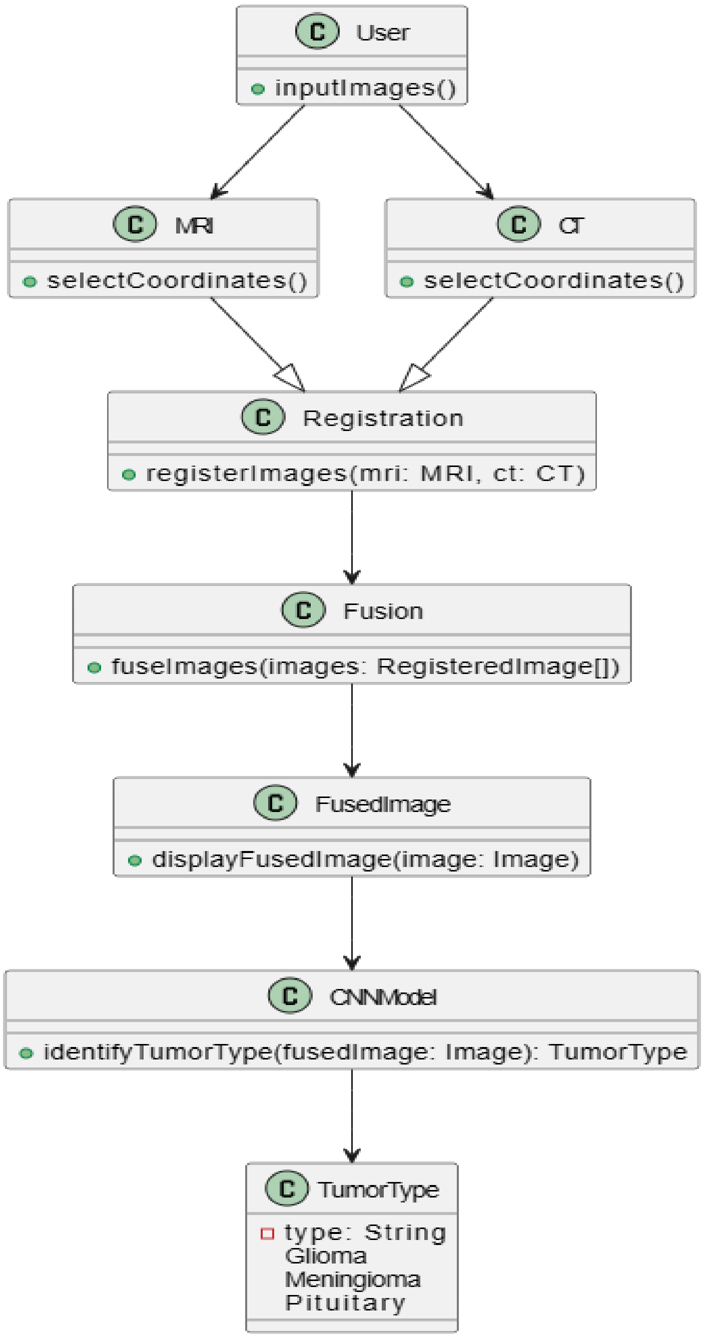

Figure 6: Class Diagram

4.3.3 Sequence Diagram

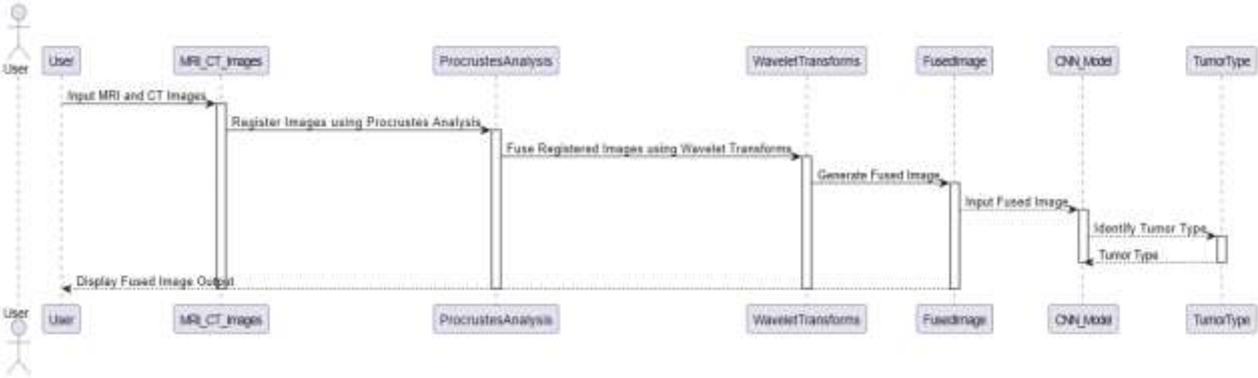

Figure 7: Sequence Diagram

4.3.4 Activity Diagram

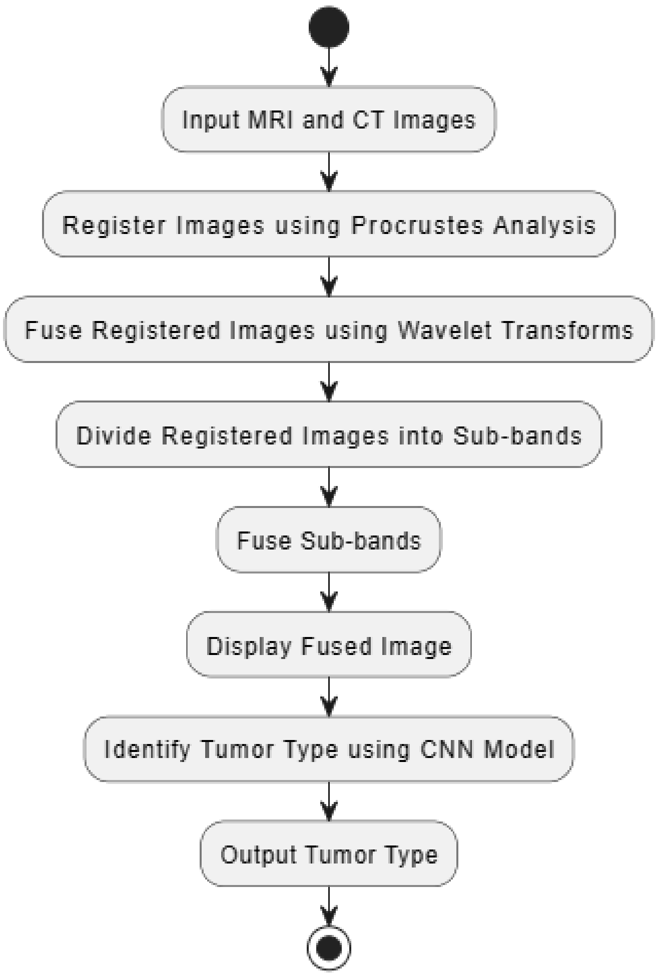

Figure 8: Activity Diagram

CHAPTER 5

IMPLEMENTATION

5.1 SOURCE CODE

Image Registration Process:

```
def procrustes(X, Y, scaling=True, reflection='best'):
    n,m = X.shape
    ny,my = Y.shape
    muX = X.mean(0)
    muY = Y.mean(0)
    X0 = X - muX
    Y0 = Y - muY
    ssX = (X0**2.).sum()
    ssY = (Y0**2.).sum()
    print(ssX)
    print(ssY)
    # centred Frobenius norm
    normX = np.sqrt(ssX)
    normY = np.sqrt(ssY)
    # scale to equal (unit) norm
    X0 /= normX
    Y0 /= normY
    if my < m:
        Y0 = np.concatenate((Y0, np.zeros(n, m-my)),0)
    # optimum rotation matrix of Y
    A = np.dot(X0.T, Y0)
    U,s,Vt = np.linalg.svd(A,full_matrices=False)
    V = Vt.T
    T = np.dot(V, U.T)
    if reflection is not 'best':
        have_reflection = np.linalg.det(T) < 0
        if reflection != have_reflection:
            V[:,-1] *= -1
            s[-1] *= -1
            T = np.dot(V, U.T)
    traceTA = s.sum()
    if scaling:
        # optimum scaling of Y
        b = traceTA * normX / normY
        # standarised distance between X and b*Y*T + c
        d = 1 - traceTA**2
```

```
        # transformed coords
        Z = normX*traceTA*np.dot(Y0, T) + muX
    else:
        b = 1
        d = 1 + ssY/ssX - 2 * traceTA * normY / normX
        Z = normY*np.dot(Y0, T) + muX
    # transformation matrix
    if my < m:
        T = T[:my,:]
    c = muX - b*np.dot(muY, T)
    tform = {'rotation':T, 'scale':b, 'translation':c}
    return d, Z, tform
import numpy as np
import cv2
import imageio
import scipy.ndimage as ndi
ct = cv2.imread('jpg/ct.jpg', 0)
ct_points=[]
mri_points=[]
n=int(input())
# Define Click Function
def click_event_ct(event, x, y, flags, param):
    if event == cv2.EVENT_LBUTTONDOWN:
        print(x,y)
        ct_points.append([x,y])
cv2.imshow('Image CT', ct)
cv2.setMouseCallback('Image CT', click_event_ct)
cv2.waitKey(0)#press any key to close all windows
cv2.destroyAllWindows()
ct_points
# Define Click Function
def click_event_mri(event, x, y, flags, param):
    if event == cv2.EVENT_LBUTTONDOWN:
        print(x,y)
        mri_points.append([x,y])
mri_registered = cv2.imread('jpg/mri.jpg',0)
cv2.imshow('Image MRI', mri_registered)
cv2.setMouseCallback('Image MRI', click_event_mri)
cv2.waitKey(0)#press any key to close all windows
cv2.destroyAllWindows()
mri_points
X_pts = np.asarray(ct_points)
Y_pts = np.asarray(mri_points)
```

```
print(X_pts)
d,Z_pts,Tform = procrustes(X_pts,Y_pts)
R = np.eye(3)
Tform
R[0:2,0:2] = Tform['rotation']
S = np.eye(3) * Tform['scale']
S[2,2] = 1
t = np.eye(3)
t[0:2,2] = Tform['translation']
M = np.dot(np.dot(R,S),t.T).T
h=ct.shape[0]
w=ct.shape[1]
tr_Y_img = cv2.warpAffine(mri_registered,M[0:2,:],(h,w))
cv2.imwrite("jpg/mri_registered.jpg", tr_Y_img)
aY_pts = np.hstack((Y_pts,np.array(([[1,1,1,1,1]])).T))
tr_Y_pts = np.dot(M,aY_pts.T).T
plt.figure()
plt.subplot(1,3,1)
plt.imshow(ct,cmap=cm.gray)
plt.plot(X_pts[:,0],X_pts[:,1],'bo',markersize=5)
plt.subplot(1,3,3)
plt.imshow(tr_Y_img,cmap=cm.gray)
plt.plot(tr_Y_pts[:,0],tr_Y_pts[:,1],'gx',markersize=5)
plt.show()
```

Image fusion Process:

```
import argparse
import cv2
import numpy as np
import torch
import torch.nn as nn
import torch.nn.functional as F
from torchvision.models.vgg import vgg19
class VGG19(torch.nn.Module):
    def __init__(self, device='cpu'):
        super(VGG19, self).__init__()
        features = list(vgg19().features)
        if device == "cuda":
            self.features = nn.ModuleList(features).cuda().eval()
        else:
            self.features = nn.ModuleList(features).eval()
    def forward(self, x):
        feature_maps = []
```

```
        for idx, layer in enumerate(self.features):
            x = layer(x)
            if idx == 3:
                feature_maps.append(x)
        return feature_maps
class Fusion:
    def __init__(self, input):
        self.input_images = input
        self.device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
        self.model = VGG19(self.device)

    def fuse(self):
        """
        A top level method which fuse self.images
        """
        # Convert all images to YCbCr format
        self.normalized_images = [-1 for img in self.input_images]
        self.YCbCr_images = [-1 for img in self.input_images]
        for idx, img in enumerate(self.input_images):
            if not self._is_gray(img):
                self.YCbCr_images[idx] = self._RGB_to_YCbCr(img)
                self.normalized_images[idx] = self.YCbCr_images[idx][:, :, 0]
            else:
                self.normalized_images[idx] = img / 255.
        # Transfer all images to PyTorch tensors
        self._tranfer_to_tensor()
        # Perform fuse strategy
        fused_img = self._fuse()[:, :, 0]
        # Reconstruct fused image given rgb input images
        for idx, img in enumerate(self.input_images):
            if not self._is_gray(img):
                self.YCbCr_images[idx][:, :, 0] = fused_img
                fused_img = self._YCbCr_to_RGB(self.YCbCr_images[idx])
                fused_img = np.clip(fused_img, 0, 1)

        return (fused_img * 255).astype(np.uint8)
        # return fused_img

    def _fuse(self):
        """
        Perform fusion algorithm
        """
        with torch.no_grad():
```

```
        imgs_sum_maps = [-1 for tensor_img in self.images_to_tensors]
        for idx, tensor_img in enumerate(self.images_to_tensors):
            imgs_sum_maps[idx] = []
            feature_maps = self.model(tensor_img)
            for feature_map in feature_maps:
                sum_map = torch.sum(feature_map, dim=1, keepdim=True)
                imgs_sum_maps[idx].append(sum_map)

        max_fusion = None
        for sum_maps in zip(*imgs_sum_maps):
            features = torch.cat(sum_maps, dim=1)
            weights = self._softmax(F.interpolate(features,
                                    size=self.images_to_tensors[0].shape[2:]))
            weights = F.interpolate(weights,
                                    size=self.images_to_tensors[0].shape[2:])
            current_fusion = torch.zeros(self.images_to_tensors[0].shape)
            for idx, tensor_img in enumerate(self.images_to_tensors):
                current_fusion += tensor_img * weights[:,idx]
            if max_fusion is None:
                max_fusion = current_fusion
            else:
                max_fusion = torch.max(max_fusion, current_fusion)

        output = np.squeeze(max_fusion.cpu().numpy())
        if output.ndim == 3:
            output = np.transpose(output, (1, 2, 0))
        return output

    def _RGB_to_YCbCr(self, img_RGB):
        """
        A private method which converts an RGB image to YCrCb format
        """
        img_RGB = img_RGB.astype(np.float32) / 255.
        return cv2.cvtColor(img_RGB, cv2.COLOR_RGB2YCrCb)

    def _YCbCr_to_RGB(self, img_YCbCr):
        """
        A private method which converts a YCrCb image to RGB format
        """
        img_YCbCr = img_YCbCr.astype(np.float32)
        return cv2.cvtColor(img_YCbCr, cv2.COLOR_YCrCb2RGB)
```

```
    def _is_gray(self, img):
            """
            A private method which returns True if image is gray, otherwise False
            """
            if len(img.shape) < 3:
                return True
            if img.shape[2] == 1:
                return True
            b, g, r = img[:,:,0], img[:,:,1], img[:,:,2]
            if (b == g).all() and (b == r).all():
                return True
            return False

    def _softmax(self, tensor):
            """
            A private method which compute softmax ouput of a given tensor
            """
            tensor = torch.exp(tensor)
            tensor = tensor / tensor.sum(dim=1, keepdim=True)
            return tensor
    def _tranfer_to_tensor(self):
            """
            A private method to transfer all input images to PyTorch tensors
            """
            self.images_to_tensors = []
            for image in self.normalized_images:
                np_input = image.astype(np.float32)
                if np_input.ndim == 2:
                    np_input = np.repeat(np_input[None, None], 3, axis=1)
                else:
                    np_input = np.transpose(np_input, (2, 0, 1))[None]
                if self.device == "cuda":
                    self.images_to_tensors.append(torch.from_numpy(np_input).cuda())
                else:
                    self.images_to_tensors.append(torch.from_numpy(np_input))
pip install PyWavelets
import numpy as np
import matplotlib.pyplot as plt
import pywt
import pywt.data
# Load MRI image
mri_image = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-image-fusion-to-detect-brain-tumors-master/dataset/Patient Data/p11/mri_registered.jpg')
```

```
mri_image = cv2.cvtColor(mri_image, cv2.COLOR_BGR2GRAY)

# Wavelet transform of image, and plot approximation and details
titles = ['Approximation', ' Horizontal detail',
          'Vertical detail', 'Diagonal detail']
coeffs2 = pywt.dwt2(mri_image, 'haar')

LL, (LH, HL, HH) = coeffs2

fig = plt.figure(figsize=(12, 3))
for i, a in enumerate([LL, LH, HL, HH]):
    ax = fig.add_subplot(1, 4, i + 1)
    ax.imshow(a, interpolation="nearest", cmap=plt.cm.gray)
     path='C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_MRI11_'
+str(i)+'.jpg'
    cv2.imwrite(path,a)
    ax.set_title(titles[i], fontsize=10)
    ax.set_xticks([])
    ax.set_yticks([])
fig.tight_layout()
plt.show()
# Load CT Image
ct_image = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-
image-fusion-to-detect-brain-tumors-master/dataset/Patient Data/p11/ct.jpg')
ct_image = cv2.cvtColor(ct_image, cv2.COLOR_BGR2GRAY)

# Wavelet transform of image, and plot approximation and details
titles = ['Approximation', ' Horizontal detail',
          'Vertical detail', 'Diagonal detail']
coeffs2 = pywt.dwt2(ct_image, 'haar')

LL, (LH, HL, HH) = coeffs2

fig = plt.figure(figsize=(12, 3))
for i, a in enumerate([LL, LH, HL, HH]):
    ax = fig.add_subplot(1, 4, i + 1)
    ax.imshow(a, interpolation="nearest", cmap=plt.cm.gray)
    path='C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_CT11_'+s
tr(i)+'.jpg'
    cv2.imwrite(path,a)
    ax.set_title(titles[i], fontsize=10)
    ax.set_xticks([])
    ax.set_yticks([])
```

```
fig.tight_layout()
plt.show()
# Load CT Image
ct_image = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-image-fusion-to-detect-brain-tumors-master/dataset/Patient Data/p11/ct.jpg')
ct_image = cv2.cvtColor(ct_image, cv2.COLOR_BGR2GRAY)

# Wavelet transform of image, and plot approximation and details
titles = ['Approximation', ' Horizontal detail',
          'Vertical detail', 'Diagonal detail']
coeffs2 = pywt.dwt2(ct_image, 'haar')

LL, (LH, HL, HH) = coeffs2

fig = plt.figure(figsize=(12, 3))
for i, a in enumerate([LL, LH, HL, HH]):
    ax = fig.add_subplot(1, 4, i + 1)
    ax.imshow(a, interpolation="nearest", cmap=plt.cm.gray)
     path='C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_CT11_'+str(i)+'.jpg'
    cv2.imwrite(path,a)
    ax.set_title(titles[i], fontsize=10)
    ax.set_xticks([])
    ax.set_yticks([])

fig.tight_layout()
plt.show()
# Calling the methods for Siamese on LL Images
input_images = []
mri = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_MRI11_0.jpg')
mri = cv2.cvtColor(mri, cv2.COLOR_BGR2GRAY)

ct = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_CT11_0.jpg')
ct = cv2.cvtColor(ct, cv2.COLOR_BGR2GRAY)

input_images.append(mri)
input_images.append(ct)

# Compute fusion image
```

```
FU = Fusion(input_images)
fusion_img = FU.fuse()
# Write fusion image
cv2.imwrite('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_fusion_0.jpg', fusion_img)

# Calling the methods for Siamese on LH Images
input_images = []
mri = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_MRI11_1.jpg')
mri = cv2.cvtColor(mri, cv2.COLOR_BGR2GRAY)

ct = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_CT11_1.jpg')
ct = cv2.cvtColor(ct, cv2.COLOR_BGR2GRAY)

input_images.append(mri)
input_images.append(ct)

# Compute fusion image
FU = Fusion(input_images)
fusion_img = FU.fuse()
# Write fusion image
cv2.imwrite('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_fusion_1.jpg', fusion_img)

# Calling the methods for Siamese on LV Images
input_images = []
mri = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_MRI11_2.jpg')
mri = cv2.cvtColor(mri, cv2.COLOR_BGR2GRAY)

ct = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_CT11_2.jpg')
ct = cv2.cvtColor(ct, cv2.COLOR_BGR2GRAY)

input_images.append(mri)
input_images.append(ct)
```

```
# Compute fusion image
FU = Fusion(input_images)
fusion_img = FU.fuse()
# Write fusion image
cv2.imwrite('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_fusion_2.jpg', fusion_img)

# Calling the methods for Siamese on LD Images
input_images = []
mri = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_MRI11_3.jpg')
mri = cv2.cvtColor(mri, cv2.COLOR_BGR2GRAY)

ct = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_CT11_3.jpg')
ct = cv2.cvtColor(ct, cv2.COLOR_BGR2GRAY)

input_images.append(mri)
input_images.append(ct)

# Compute fusion image
FU = Fusion(input_images)
fusion_img = FU.fuse()
# Write fusion image
cv2.imwrite('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_fusion_3.jpg', fusion_img)

fusion_0 = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_fusion_0.jpg')
fusion_0 = cv2.cvtColor(fusion_0, cv2.COLOR_BGR2GRAY)

fusion_1 = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_fusion_1.jpg')
fusion_1 = cv2.cvtColor(fusion_1, cv2.COLOR_BGR2GRAY)

fusion_2 = cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_fusion_2.jpg')
fusion_2 = cv2.cvtColor(fusion_2, cv2.COLOR_BGR2GRAY)
```

```
fusion_3 =
cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_fusion_3.jpg')
fusion_3 = cv2.cvtColor(fusion_3, cv2.COLOR_BGR2GRAY)
coeffs=(fusion_0,(fusion_1,fusion_2,fusion_3))
fusion=pywt.idwt2(coeffs,'haar')
cv2.imwrite('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_final_fusion.jpg',fusion)
```

Detection and Classification Process:

```
pip install seaborn
import os
import itertools
import numpy as np
import pandas as pd
import seaborn as sns
sns.set_style('darkgrid')
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
import cv2 as cv

# import Deep learning Libraries
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adamax
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
import warnings
warnings.filterwarnings('ignore')
train_data_dir = 'C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-image-fusion-to-detect-brain-tumors-master/archive/Training'
filepaths = []
labels = []
folds = os.listdir(train_data_dir)

for fold in folds:
    foldpath = os.path.join(train_data_dir, fold)
    filelist = os.listdir(foldpath)
    for file in filelist:
        fpath = os.path.join(foldpath, file)
```

```
        filepaths.append(fpath)
        labels.append(fold)

# Concatenate data paths with labels into one dataframe
Fseries = pd.Series(filepaths, name= 'filepaths')
Lseries = pd.Series(labels, name='labels')

train_df = pd.concat([Fseries, Lseries], axis= 1)
train_df
# Generate data paths with labels
train_data_dir = 'C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-image-fusion-to-detect-brain-tumors-master/archive/Testing'
filepaths = []
labels = []

folds = os.listdir(train_data_dir)

for fold in folds:
    foldpath = os.path.join(train_data_dir, fold)
    filelist = os.listdir(foldpath)
    for file in filelist:
        fpath = os.path.join(foldpath, file)

        filepaths.append(fpath)
        labels.append(fold)

# Concatenate data paths with labels into one dataframe
Fseries = pd.Series(filepaths, name= 'filepaths')
Lseries = pd.Series(labels, name='labels')

ts_df = pd.concat([Fseries, Lseries], axis= 1)
ts_df
data_balance = train_df.labels.value_counts()
def custom_autopct(pct):
    total = sum(data_balance)
    val = int(round(pct*total/100.0))
    return "{:.1f}%\n({:d})".format(pct, val)
# pie chart for data balance
plt.pie(data_balance, labels = data_balance.index, autopct=custom_autopct, colors = ["#2092E6","#6D8CE6","#20D0E6","#A579EB"])
plt.title("Training data balance")
plt.axis("equal")
```

```
plt.show()
# valid and test dataframe
valid_df, test_df = train_test_split(ts_df,  train_size= 0.5, shuffle= True, random_state= 42)
# crobed image size
batch_size = 16
img_size = (224, 224)

tr_gen = ImageDataGenerator()
ts_gen = ImageDataGenerator()

train_gen = tr_gen.flow_from_dataframe( train_df, x_col= 'filepaths', y_col= 'labels', target_size= img_size, class_mode= 'categorical',
                                      color_mode= 'rgb', shuffle= True, batch_size= batch_size)

valid_gen = ts_gen.flow_from_dataframe( valid_df, x_col= 'filepaths', y_col= 'labels', target_size= img_size, class_mode= 'categorical',
                                      color_mode= 'rgb', shuffle= True, batch_size= batch_size)

test_gen = ts_gen.flow_from_dataframe( test_df, x_col= 'filepaths', y_col= 'labels', target_size= img_size, class_mode= 'categorical',
                                      color_mode= 'rgb', shuffle= False, batch_size= batch_size)
g_dict = train_gen.class_indices
classes = list(g_dict.keys())
images, labels = next(train_gen)


plt.figure(figsize= (20, 20))

for i in range(16):
    plt.subplot(4, 4, i + 1)
    image = images[i] / 255
    plt.imshow(image)
    index = np.argmax(labels[i])
    class_name = classes[index]
    plt.title(class_name, color= 'black', fontsize= 16)
    plt.axis('off')
plt.tight_layout()
plt.show()
# Create Model Structure
img_size = (224, 224)
channels = 3
img_shape = (img_size[0], img_size[1], channels)
```

```
class_count = len(list(train_gen.class_indices.keys()))

model = Sequential()

model.add(Conv2D(filters=32, kernel_size=(3,3), padding="same", activation="relu",
input_shape= img_shape))
model.add(MaxPooling2D())

model.add(Conv2D(filters=64, kernel_size=(3,3), padding="same", activation="relu"))
model.add(MaxPooling2D())

model.add(Flatten())

model.add(Dense(64,activation = "relu"))
model.add(Dense(32,activation = "relu"))
model.add(Dense(class_count, activation = "softmax"))
model.compile(Adamax(learning_rate= 0.001), loss= 'categorical_crossentropy', metrics=
['accuracy'])

model.summary()
epochs = 10
history = model.fit(train_gen, epochs= epochs, verbose= 1, validation_data= valid_gen, shuffle=
False)
# Define needed variables
tr_acc = history.history['accuracy']
tr_loss = history.history['loss']
val_acc = history.history['val_accuracy']
val_loss = history.history['val_loss']
index_loss = np.argmin(val_loss)
val_lowest = val_loss[index_loss]
index_acc = np.argmax(val_acc)
acc_highest = val_acc[index_acc]

Epochs = [i+1 for i in range(len(tr_acc))]
loss_label = f'best epoch= {str(index_loss + 1)}'
acc_label = f'best epoch= {str(index_acc + 1)}'

# Plot training history
plt.figure(figsize= (20, 8))
plt.style.use('fivethirtyeight')

plt.subplot(1, 2, 1)
```

```
plt.plot(Epochs, tr_loss, 'r', label= 'Training loss')
plt.plot(Epochs, val_loss, 'g', label= 'Validation loss')
plt.scatter(index_loss + 1, val_lowest, s= 150, c= 'blue', label= loss_label)
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(Epochs, tr_acc, 'r', label= 'Training Accuracy')
plt.plot(Epochs, val_acc, 'g', label= 'Validation Accuracy')
plt.scatter(index_acc + 1 , acc_highest, s= 150, c= 'blue', label= acc_label)
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.tight_layout
plt.show()
train_score = model.evaluate(train_gen, verbose= 1)
valid_score = model.evaluate(valid_gen, verbose= 1)
test_score = model.evaluate(test_gen, verbose= 1)

print("Train Loss: ", train_score[0])
print("Train Accuracy: ", train_score[1])
print('-' * 20)
print("Validation Loss: ", valid_score[0])
print("Validation Accuracy: ", valid_score[1])
print('-' * 20)
print("Test Loss: ", test_score[0])
print("Test Accuracy: ", test_score[1])
preds = model.predict(test_gen)
y_pred = np.argmax(preds, axis=1)
g_dict = test_gen.class_indices
classes = list(g_dict.keys())

cm = confusion_matrix(test_gen.classes, y_pred)
cm

plt.figure(figsize= (10, 10))
plt.imshow(cm, interpolation= 'nearest', cmap= plt.cm.Blues)
plt.title('Confusion Matrix')
plt.colorbar()

tick_marks = np.arange(len(classes))
```

```
plt.xticks(tick_marks, classes, rotation= 45)
plt.yticks(tick_marks, classes)
thresh = cm.max() / 2.
for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
    plt.text(j, i, cm[i, j], horizontalalignment= 'center', color= 'white' if cm[i, j] > thresh else 'black')

plt.tight_layout()
plt.ylabel('True Label')
plt.xlabel('Predicted Label')
plt.show()
# Classification report
print(classification_report(test_gen.classes, y_pred, target_names= classes))
#Save the model
model.save('C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-image-fusion-to-detect-brain-tumors-master/Brain Tumor.h5')
loaded_model = tf.keras.models.load_model('Brain Tumor.h5', compile=False)
loaded_model.compile(Adamax(learning_rate= 0.001), loss= 'categorical_crossentropy', metrics= ['accuracy'])
image_path = 'C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-image-fusion-to-detect-brain-tumors-master/dataset/Patient Data/p37/mri.jpg'
image = cv.imread(image_path)

# Preprocess the image
shape_array=image.shape
img=cv.resize(image,(224,224))
#img = image.resize((224, 224))
img_array = tf.keras.preprocessing.image.img_to_array(img)
img_array = tf.expand_dims(img_array, 0)

# Make predictions
predictions = loaded_model.predict(img_array)
class_labels = ['Glioma', 'Meningioma', 'No Tumor', 'Pituitary']
print(f"{class_labels[np.argmax(predictions)]}")
plt.imshow(img,cmap='gray')
#plt.title(predicted)
plt.axis('off')
def classification():
    loaded_model = tf.keras.models.load_model('Brain Tumor.h5', compile=False)
        loaded_model.compile(Adamax(learning_rate= 0.001), loss= 'categorical_crossentropy', metrics= ['accuracy'])
        image=cv.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-image-fusion-to-detect-brain-tumors-master/dataset/Patient Data/p38/mri.jpg')
```

```
    # Preprocess the image
    shape_array=image.shape
    img=cv.resize(image,(224,224))
    #img = image.resize((224, 224))
    img_array = tf.keras.preprocessing.image.img_to_array(img)
    img_array = tf.expand_dims(img_array, 0)

    # Make predictions
    predictions = loaded_model.predict(img_array)
    class_labels = ['Glioma', 'Meningioma', 'No Tumor', 'Pituitary']
    print(f"{class_labels[np.argmax(predictions)]}")
    plt.imshow(img,cmap='gray')
    #plt.title(predicted)
    plt.axis('off')
classification()
```

HTML FILES:

base.html

```
<!DOCTYPE html>
<html lang="en">

<head>
    <meta charset="UTF-8">
    <title>MMMIF</title>
    {% block link %}{% endblock %}
    {% block script %}{% endblock %}
</head>

<body>
    {% block body %}{% endblock %}
</body>

</html>
```

form.html

```
<!DOCTYPE html>
<html lang="en">

<head>
    <meta charset="UTF-8">
    <title>MMMIF</title>
```

```
<link rel="stylesheet" href="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/css/bootstrap.min.css"
integrity="sha384-Vkoo8x4CGsO3+Hhxv8T/Q5PaXtkKtu6ug5TOeNV6gBiFeWPGFN9MuhOf23Q9Ifjh"
crossorigin="anonymous">
    <link rel="stylesheet" href="../static/css/form.css">

</head>

<body>
    <div class="container-fluid">
        <div class="landing-content text-center">
            <h1><font size="20">Welcome to Diagnose Support Hub</font></h1>
            <p style="border:4px solid Gray;"><font size="6" style="background:MediumSeaGreen;">Providing Comprehensive Medical Solutions</font></p>
        </div>
    </div>
    <div class="container">
        <div class="row justify-content-center">
            <div class="col-lg-6 col-md-8 col-sm-10">
                <div style="background: rgba(0, 0, 0, 0.7); padding: 20px; border-radius: 10px;">
                    <h3 class="text-center">Landmark-Based Registration</h3>
                    <form id="upload-form" action="{{ url_for('upload') }}" method="POST" enctype="multipart/form-data">
                        <div class="form-group">
                            <label for="mri">Select MRI Image :</label>
                            <input type="file" name="mri" id="mri" accept="image/*" class="form-control" required>
                        </div>

                        <div class="form-group">
                            <label for="ct">Select CT Image :</label>
                            <input type="file" name="ct" id="ct" accept="image/*" class="form-control" required>
                        </div>

                        <div class="form-group">
                            <label for="points">Enter Number of Points for Registration (Min 5, Max 10) :</label>
                            <input type="number" name="points" min="5" max="10" class="form-control" required>
                        </div>
```

```
                    <input type="submit" value="Upload Files" class="btn btn-primary btn-block">
                </form>
            </div>
        </div>
    </div>
</div>

<div class="container-fluid text-center mt-5">
    <div class="quote-text">
        <blockquote class="blockquote">
            <p class="mb-0"><font size="6">"The art of medicine consists of amusing the patient
while nature cures the disease." - Voltaire</font></p>
        </blockquote>
    </div>
</div>

<script src="https://code.jquery.com/jquery-3.4.1.slim.min.js"
                                                                    integrity="sha384-
J6qa4849blE2+poT4WnyKhv5vZF5SrPo0iEjwBvKU7imGFAV0wwj1yYfoRSJoZ+n"
        crossorigin="anonymous"></script>
<script src="https://cdn.jsdelivr.net/npm/popper.js@1.16.0/dist/umd/popper.min.js"
                                                                    integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
        crossorigin="anonymous"></script>
<script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"
                                                                    integrity="sha384-
wfSDF2E50Y2D1uUdj0O3uMBJnjuUD4Ih7YwaYd1iqfktj0Uod8GCExl3Og8ifwB6"
        crossorigin="anonymous"></script>
</body>
</html>
```

registration.html

```
{% extends 'base.html' %}

{% block link %}
<link                                                                    rel="stylesheet"
href="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/css/bootstrap.min.css"
                                                                    integrity="sha384-
Vkoo8x4CGsO3+Hhxv8T/Q5PaXtkKtu6ug5TOeNV6gBiFeWPGFN9MuhOf23Q9Ifjh"
crossorigin="anonymous">
<link rel="stylesheet" href="{{ url_for('static',filename='css/registration.css') }}">
```

```
{% endblock %}

{% block script %}
<script src="https://code.jquery.com/jquery-3.4.1.min.js"
            integrity="sha256-CSXorXvZcTkaix6Yvo6HppcZGetbYMGWSFlBw8HfCJo="
crossorigin="anonymous"></script>
<script type="text/javascript" src="{{ url_for('static',filename='js/coord.js') }}"></script>
<script src="https://cdn.jsdelivr.net/npm/popper.js@1.16.0/dist/umd/popper.min.js"
                                                                    integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
  crossorigin="anonymous"></script>
<script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"
                                                                    integrity="sha384-
wfSDF2E50Y2D1uUdj0O3uMBJnjuUD4Ih7YwaYd1iqfktj0Uod8GCExl3Og8ifwB6"
  crossorigin="anonymous"></script>
{% endblock %}

{% block body %}

<!DOCTYPE html>
<html lang="en">

<head>
  <meta charset="UTF-8">
  <title>MMMIF</title>
</head>
<body>

  <div class="container">
    <div class="row">
      <div class="col-lg-12">
        <center>
            <h2 style="margin-top:40px;margin-bottom:20px"><font size="10">Select Co-
ordinates for Registration Process</font></h2>
        </center>
      </div>
    </div>
    <div class="row">
      <div class="col-lg-6 col-md-12 col-sm-12">
          <div style="display: flex;flex-direction: column;align-items:center; justify-content:
space-between;min-height:662px;">
          <h2 style="margin-top: 20px;">MRI Image</h2>
          <img src="{{ url_for('static',filename='mri.jpg') }}" id="mri" alt="MRI" class="mri"
```

```
                style="border:2px solid #87857f;padding:15px; border-radius:10px;">
              <div>
                <p>MRI X:<span id="mriX"></span></p>
                <p>MRI Y:<span id="mriY"></span></p>
              </div>
            </div>
          </div>
          <div class="col-lg-6 col-md-12 col-sm-12">
                <div style="display: flex;flex-direction: column;align-items: center;justify-
content:space-between;min-height: 662px;">
              <h2 style="margin-top: 20px;">CT Image</h2>
              <img src="{{ url_for('static',filename='ct.jpg') }}" id="ct" alt="CT" class="ct"
                style="border:2px solid #87857f;padding:15px; border-radius:10px;">
              <div>
                <p>CT X:<span id="ctX"></span></p>
                <p>CT Y:<span id="ctY"></span></p>
              </div>
            </div>
          </div>
        </div>

        <div class="row">
          <div class="col-lg-12">
            <center>
              <button onclick="sendParameters()" class="btn btn-primary" style="margin-bottom:
40px;">Submit
                Data</button>
            </center>
          </div>
        </div>
    </div>

    <script type="text/javascript">
        var myImgMri = document.getElementById("mri");
        var points = {{ points }};
        myImgMri.onclick = GetCoordinatesMri;

        var myImgCt = document.getElementById("ct");
        myImgCt.onclick = GetCoordinatesCt;
    </script>
</body>

</html>
```

```
{% endblock %}
```

imageregistration.html

```
<!DOCTYPE html>
<html lang="en">

<head>
    <meta charset="UTF-8">
    <title>MMMIF</title>
                                                                        <link                                    rel="stylesheet"
href="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/css/bootstrap.min.css"
                                                                                                                          integrity="sha384-
Vkoo8x4CGsO3+Hhxv8T/Q5PaXtkKtu6ug5TOeNV6gBiFeWPGFN9MuhOf23Q9Ifjh"
crossorigin="anonymous">
    <link rel="stylesheet" href="{{ url_for('static',filename='css/registered.css') }}">
    <style>
    @keyframes page-load {
        from {
        width: 0;
        }
        to {
        width: 100%;
        }
    }
    .page-loading::before {
        content: " ";
        display: block;
        position: fixed;
        z-index: 10;
        height: 5px;
        width: 100%;
        top: 0;
        left: 0;
        background-color: #06D;
        animation: page-load ease-out 2s;
    }
    </style>
    <script>
    document.addEventListener("DOMContentLoaded", function () {
        var linksToAnimate = document.querySelectorAll(".load-animation-link");

        linksToAnimate.forEach(function (link) {
            link.addEventListener("click", function (e) {
```

```
            document.body.classList.add("page-loading");

            window.addEventListener("DOMContentLoaded", function () {
                document.body.classList.remove("page-loading");
                });
            });
        });
        window.addEventListener("beforeunload", function () {
            document.body.classList.add("page-loading");
        });
    });
</script>

</head>

<body>
    <div class="container">
        <div class="jumbotron">
            <h1 class="display-4"> <font size="10">Image Registration </font></h1>

        </div>

        <div class="row">
            <div class="col-lg-6 col-md-12 col-sm-12 content">
                <h2><font size="6">Registered MRI Image</font></h2>
                <center>
                     <img src="{{ url_for('static',filename='mri_registered.jpg') }}" id="mri" alt="MRI"
class="mri"
                        style="border:2px solid #87857f;padding:15px; border-radius:10px;">
                </center>
            </div>
            <div class="col-lg-6 col-md-12 col-sm-12 content">
                <h2><font size="6">Registered CT Image</font></h2>
                <center>
                    <img src="{{ url_for('static',filename='ct.jpg') }}" id="ct" alt="CT" class="ct"
                        style="border:2px solid #87857f;padding:15px; border-radius:10px;">
                </center>
            </div>
        </div>



        <div class="row" style="margin-bottom: 40px;">
            <div class="col-lg-12 col-md-12 col-sm-12">
```

```
            <center>
                <form action="{{ url_for('fusion') }}" method="GET">
                    <input type="submit" value="View The Fused Image" class="btn btn-primary btn-
blink" class="load-animation-link">
                </form>
            </center>
        </div>
    </div>
</div>

<script src="https://code.jquery.com/jquery-3.4.1.slim.min.js"
                                                                                integrity="sha384-
J6qa4849blE2+poT4WnyKhv5vZF5SrPo0iEjwBvKU7imGFAV0wwj1yYfoRSJoZ+n"
        crossorigin="anonymous"></script>
    <script src="https://cdn.jsdelivr.net/npm/popper.js@1.16.0/dist/umd/popper.min.js"
                                                                                integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
        crossorigin="anonymous"></script>
    <script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"
                                                                                integrity="sha384-
wfSDF2E50Y2D1uUdj0O3uMBJnjuUD4Ih7YwaYd1iqfktj0Uod8GCExl3Og8ifwB6"
        crossorigin="anonymous"></script>
</body>

</html>
```

fusion.html

```
<!DOCTYPE html>
<html lang="en">

<head>
    <meta charset="UTF-8">
    <title>MMMIF</title>
                                                    <link                    rel="stylesheet"
href="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/css/bootstrap.min.css"
                                                                                integrity="sha384-
Vkoo8x4CGsO3+Hhxv8T/Q5PaXtkKtu6ug5TOeNV6gBiFeWPGFN9MuhOf23Q9Ifjh"
crossorigin="anonymous">
    <link rel="stylesheet" href="{{ url_for('static',filename='css/registered.css') }}">
    <style>
    @keyframes page-load {
        from {
```

```
        width: 0;
        }
        to {
        width: 100%;
        }
    }
    .page-loading::before {
        content: " ";
        display: block;
        position: fixed;
        z-index: 10;
        height: 5px;
        width: 100%;
        top: 0;
        left: 0;
        background-color: #06D;
        animation: page-load ease-out 2s;
    }
    </style>
    <script>
    document.addEventListener("DOMContentLoaded", function () {
        var linksToAnimate = document.querySelectorAll(".load-animation-link");

        linksToAnimate.forEach(function (link) {
            link.addEventListener("click", function (e) {
            document.body.classList.add("page-loading");
            window.addEventListener("DOMContentLoaded", function () {
                document.body.classList.remove("page-loading");
                });
            });
        });
        window.addEventListener("beforeunload", function () {
            document.body.classList.add("page-loading");
        });
    });
</script>

</head>

<body>
    <div class="container">
        <div class="jumbotron">
            <h1 class="display-4"> <font size="10">Image Registration </font></h1>
```

```
        </div>

        <div class="row">
            <div class="col-lg-6 col-md-12 col-sm-12 content">
                <h2><font size="6">Registered MRI Image</font></h2>
                <center>
                     <img src="{{ url_for('static',filename='mri_registered.jpg') }}" id="mri" alt="MRI"
class="mri"
                        style="border:2px solid #87857f;padding:15px; border-radius:10px;">
                </center>
            </div>
            <div class="col-lg-6 col-md-12 col-sm-12 content">
                <h2><font size="6">Registered CT Image</font></h2>
                <center>
                    <img src="{{ url_for('static',filename='ct.jpg') }}" id="ct" alt="CT" class="ct"
                        style="border:2px solid #87857f;padding:15px; border-radius:10px;">
                </center>
            </div>
        </div>


        <div class="row" style="margin-bottom: 40px;">
            <div class="col-lg-12 col-md-12 col-sm-12">
                <center>
                    <form action="{{ url_for('fusion') }}" method="GET">
                        <input type="submit" value="View The Fused Image" class="btn btn-primary btn-
blink" class="load-animation-link">
                    </form>
                </center>
            </div>
        </div>
    </div>

    <script src="https://code.jquery.com/jquery-3.4.1.slim.min.js"
                                                                        integrity="sha384-
J6qa4849blE2+poT4WnyKhv5vZF5SrPo0iEjwBvKU7imGFAV0wwj1yYfoRSJoZ+n"
        crossorigin="anonymous"></script>
    <script src="https://cdn.jsdelivr.net/npm/popper.js@1.16.0/dist/umd/popper.min.js"
                                                                        integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
        crossorigin="anonymous"></script>
    <script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"
```

```
                                                        integrity="sha384-
wfSDF2E50Y2D1uUdj0O3uMBJnjuUD4Ih7YwaYd1iqfktj0Uod8GCExl3Og8ifwB6"
        crossorigin="anonymous"></script>
</body>

</html>
```

classification.html

```
<!DOCTYPE html>
<html lang="en">

<head>
    <meta charset="UTF-8">
    <title>MMMIF</title>
                                    <link                 rel="stylesheet"
href="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/css/bootstrap.min.css"
                                                        integrity="sha384-
Vkoo8x4CGsO3+Hhxv8T/Q5PaXtkKtu6ug5TOeNV6gBiFeWPGFN9MuhOf23Q9Ifjh"
crossorigin="anonymous">
    <link rel="stylesheet" href="{{ url_for('static',filename='css/classified.css') }}">

</head>

<body>

    <div class="container">
        <div class="row">
            <div class="col-lg-12 col-md-12 col-sm-12 content">
                <div class="jumbotron">
            <h1>   </h1>

                        <h1   class="display-4"   style="color:white;"><font   size="10">Image
Classification</font></h1>

                </div>

                    <img src="{{ url_for('static',filename='classified.jpg') }}" id="fusion" alt="Fused
Image"
                        class="fusion"  style="border:2px  solid  #87857f;padding:15px;  border-
radius:10px;">
            <h3 style="color:white;"> {{predicted_text }}</h3>
```

```
            </div>
        </div>
    </div>

    <script src="https://code.jquery.com/jquery-3.4.1.slim.min.js"
                                                                                integrity="sha384-
J6qa4849blE2+poT4WnyKhv5vZF5SrPo0iEjwBvKU7imGFAV0wwj1yYfoRSJoZ+n"
        crossorigin="anonymous"></script>
    <script src="https://cdn.jsdelivr.net/npm/popper.js@1.16.0/dist/umd/popper.min.js"
                                                                                integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
        crossorigin="anonymous"></script>
    <script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"
                                                                                integrity="sha384-
wfSDF2E50Y2D1uUdj0O3uMBJnjuUD4Ih7YwaYd1iqfktj0Uod8GCExl3Og8ifwB6"
        crossorigin="anonymous"></script>
</body>

</html>
```

CSS FILES:
classified.css

```
*{
    padding: 0;
    margin:0;
    font-family: serif;
}

.content{
    margin-top: 40px;
    margin-bottom: 40px;
}
.jumbotron .display-4{
    font-size: 40px;
}
.heading{
    font-size: 25px;
    text-align: center;
}

body {
```

```
    background-image: url(../images/generated_4.png);
    background-size: cover;
    background-position: center;
}

.jumbotron {
    background-color: transparent;
     color: black;
}
```

form.css

```
*{
    padding: 0;
    margin:0;
    font-family: serif;
}

div.content{
    height: 100vh;
}
body {
    animation: backgroundAnimation 10s infinite;
    color: white;
    font-family: Arial, sans-serif;
}

@keyframes backgroundAnimation {
    0% {
    background-image: url(../images/medical30.png);
    }

    33% {
    background-image: url(../images/medical29.jpeg);
    }

    66% {
    background-image: url(../images/medical28.png);
    }

    100% {
    background-image: url(../images/medical30.png);
}
}
```

```css
.container-fluid {
    display: flex;
    justify-content: center;
    align-items: center;
    height: 100vh;
}

.landing-content {
    animation: fadeInAnimation 2s ease-in;
}

@keyframes fadeInAnimation {
    0% {
        opacity: 0;
    }

    100% {
        opacity: 1;
    }
}

.quote-text {
    animation: blinkAnimation 1s infinite;
}

@keyframes blinkAnimation {
    0% {
        opacity: 0;
    }

    50% {
        opacity: 1;
    }

    100% {
        opacity: 0;
    }
}
div.landing-content{
    margin:75px auto;
    z-index: 1;
    color:#fff;
```

```
}

div.landing-content h2{
    font-weight: 700;
    text-shadow: 2px 2px #474242;
    text-align: center;
}

div.landing-content p{
    font-weight: 600;
    padding: 30px;
    font-size: 20px;
    color:#00011a;
}
```

fusion.css

```
*{
    padding: 0;
    margin:0;
    font-family: serif;
}

.content{
    margin-top: 40px;
    margin-bottom: 40px;
}
.jumbotron .display-4{
    font-size: 28px;
}
.heading{
    font-size: 22px;
    text-align: center;
}
body {
    background-image: url(../images/generated_2.png);
    background-size: cover;
}

.jumbotron {
    background-color: transparent;
    color: #ffffff;
    animation: slideInDown 1s ease-in-out;
```

```
}

@keyframes slideInDown {
    from {
        transform: translateY(-100%);
        opacity: 0;
    }
    to {
        transform: translateY(0);
        opacity: 1;
    }
}
.content {
    animation: fadeIn 1s ease-in-out;
}

@keyframes fadeIn {
    from {
        opacity: 0;
    }
    to {
        opacity: 1;
    }
}
```

registered.css:

```
*{
    padding: 0;
    margin:0;
    font-family: serif;
}

.content{
    margin-bottom: 20px;
    margin-top: 20px;
}

h2{
    font-size: 22px;
    text-align: center;
}

.jumbotron{
```

```
    margin-top: 40px;
}

.jumbotron .display-4{
    font-size: 28px;
}

body {
    background-image: url(../images/fusion.jpeg);
    background-size: cover;
}
.jumbotron {
    background-color: transparent;
    color: #ffffff;
    animation: zoomIn 1s ease-in-out;
}

@keyframes zoomIn {
    from {
        opacity: 0;
        transform: scale(0.5);
    }
    to {
        opacity: 1;
        transform: scale(1);
    }
}

.content h2 {
    color:rgba(35, 142, 92, 0.751);
    animation: fadeInRight 1s ease-in-out;
}

@keyframes fadeInRight {
    from {
        opacity: 0;
        transform: translateX(-50px);
    }
    to {
        opacity: 1;
        transform: translateX(0);
    }
}
```

```
@keyframes blink {
    0% { opacity: 1; }
    50% { opacity: 0; }
    100% { opacity: 1; }
}

.btn-blink {
    animation: blink 1s infinite;
}
```

registration.css

```
*{
    margin: 0;
    padding: 0;
    font-family: serif;
}

h2{
    font-size: 22px;;
}
body {
    background-image: url(../images/medical24.jpeg);
    background-size: cover;
}

h2 {
    animation: shake 0.5s infinite alternate;
}

@keyframes shake {
    from {
        transform: translateX(0);
    }

    to {
        transform: translateX(5px);
    }
}

.btn-primary:hover {
    background-color: green;}
```

CHAPTER 6

RESULTS

Figure 9: Website Home page

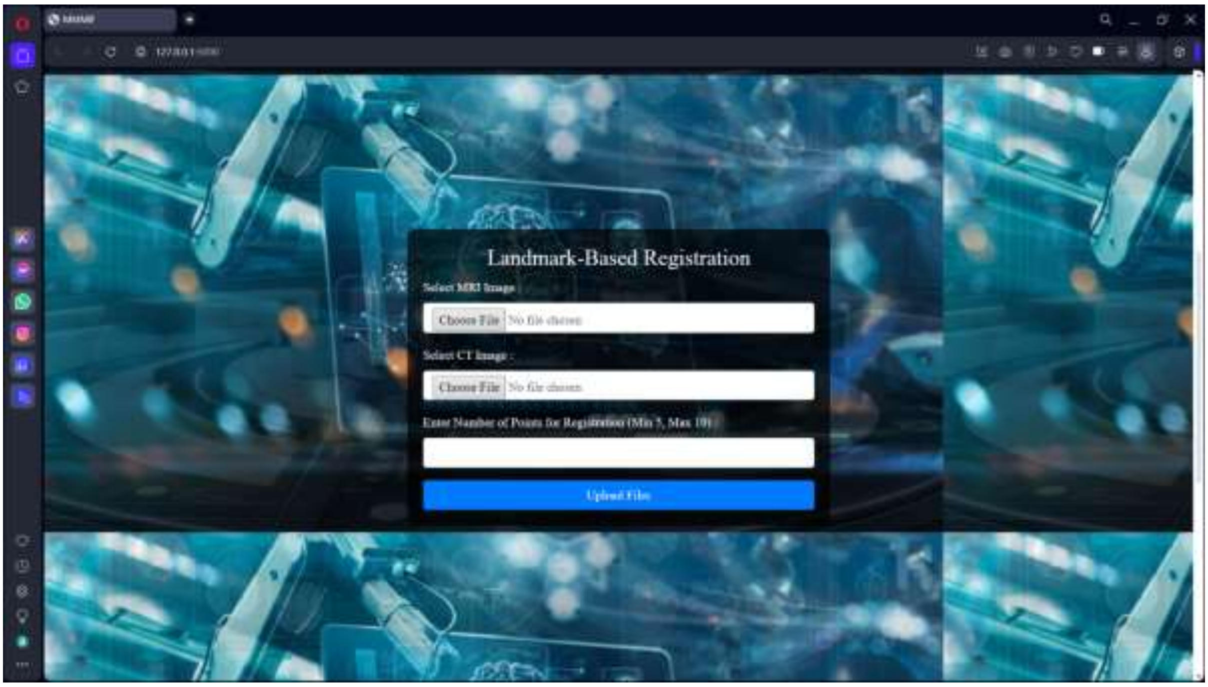

Figure 10: Landmark-Based Registration

Figure 11: Selecting Co-ordinates for Registration Process

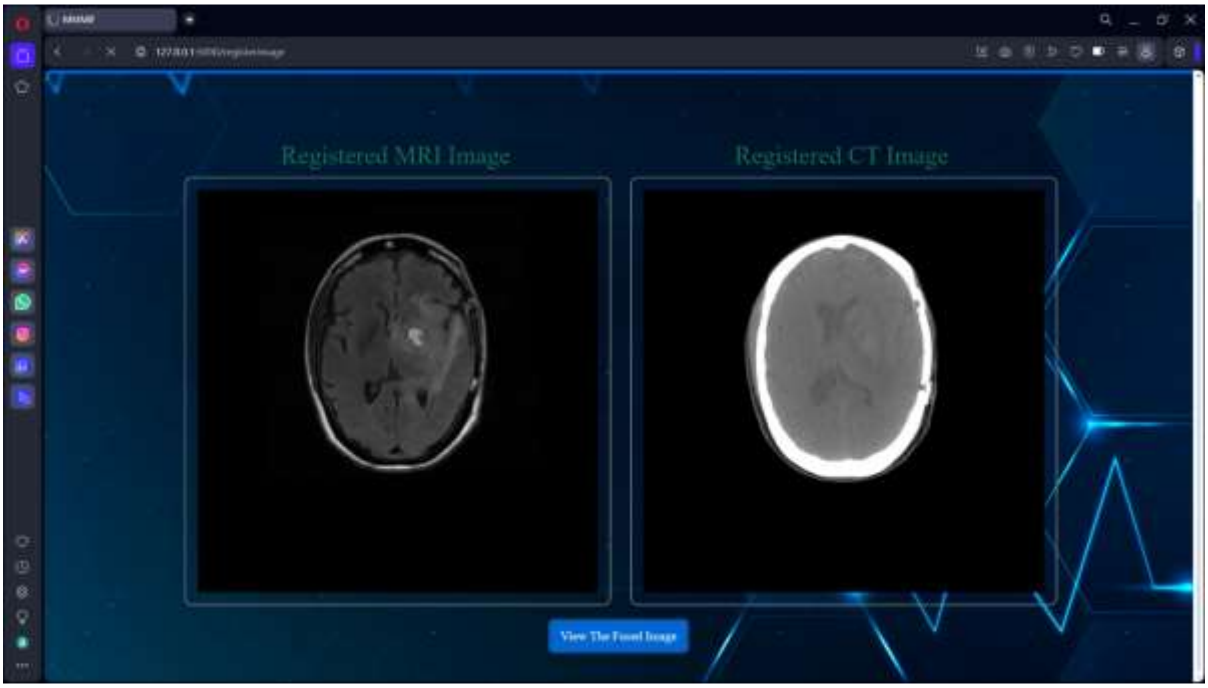

Figure 12: Registered Image

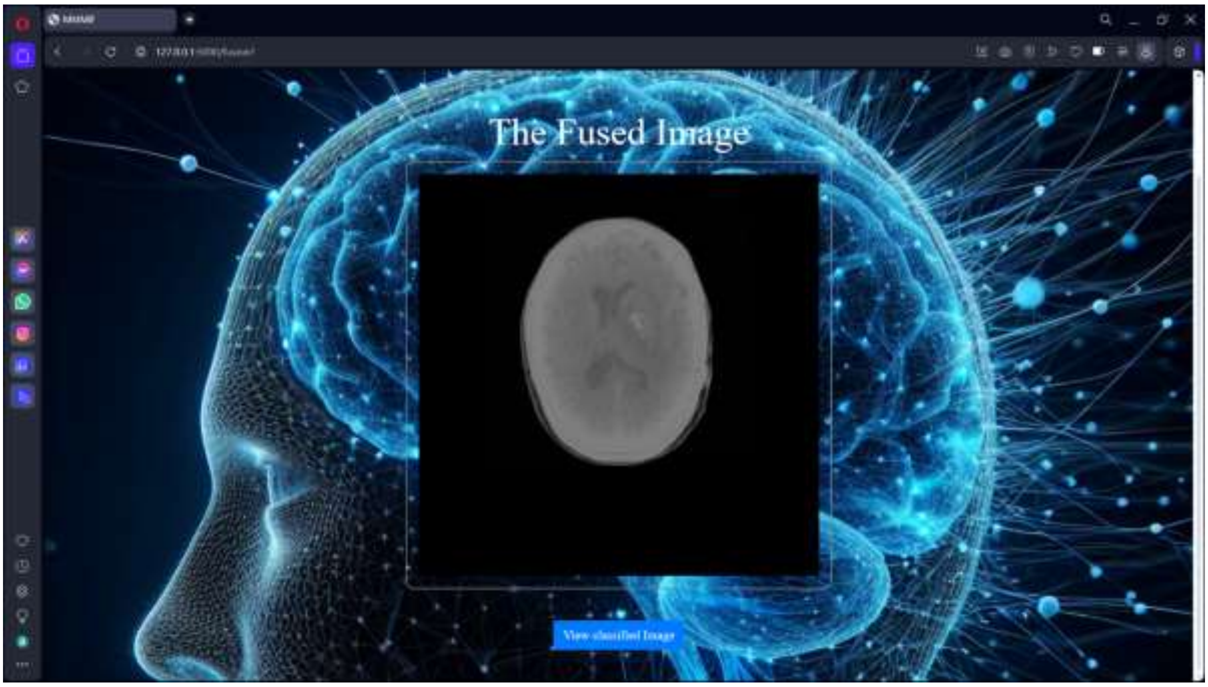

Figure 13: Fused Image

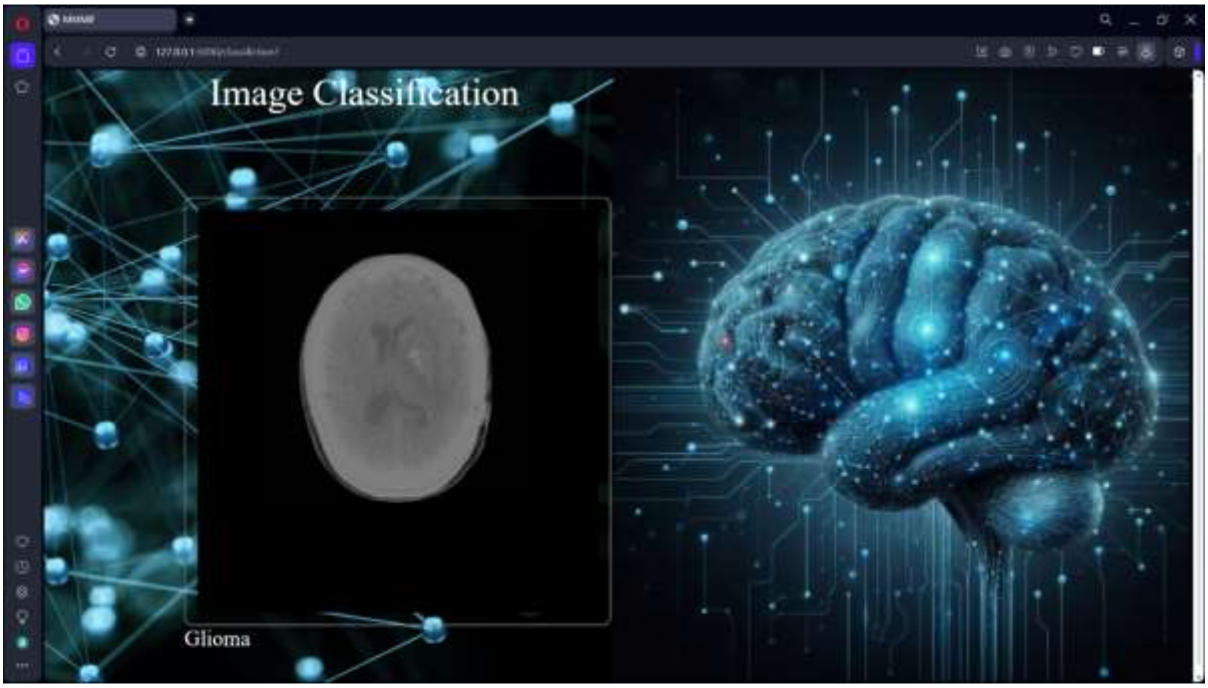

Figure 14: Classified Image

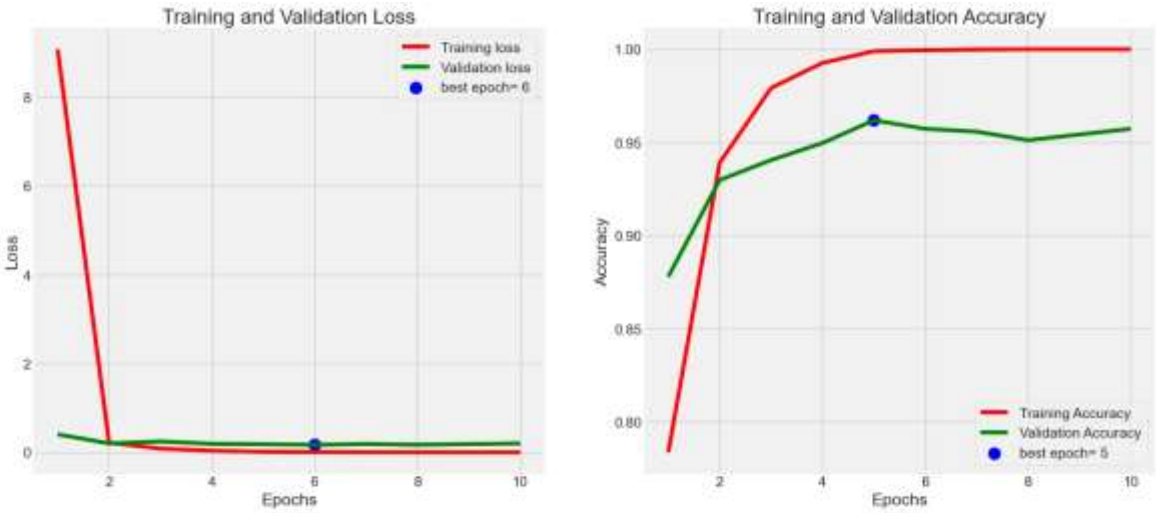

Figure 15: Proposed Model Loss and Accuracy

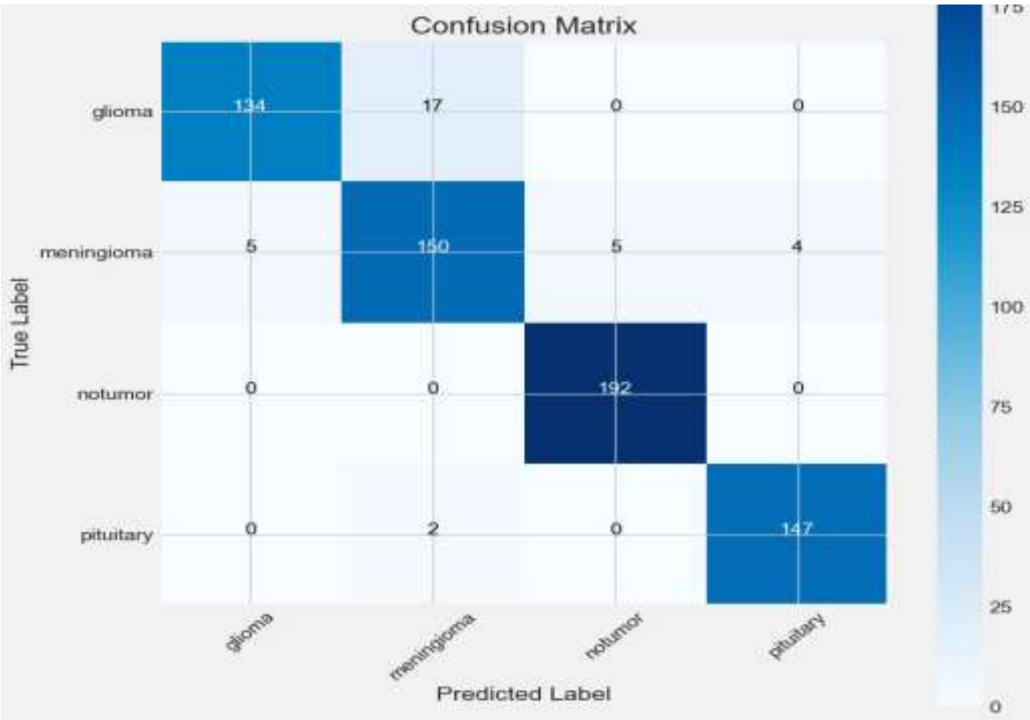

Figure 16: Confusion Matrix

	precision	recall	f1-score	support
glioma	0.96	0.89	0.92	151
meningioma	0.89	0.91	0.90	164
notumor	0.97	1.00	0.99	192
pituitary	0.97	0.99	0.98	149
accuracy			0.95	656
macro avg	0.95	0.95	0.95	656
weighted avg	0.95	0.95	0.95	656

Figure 17: Proposed System Evaluation Metrics

CHAPTER 7

CONCLUSION

In Conclusion, this study emphasizes the transformative ability of multimodal fusion techniques in revolutionizing scientific imaging, especially within the critical area of brain tumor detection. By integrating records from various resources which include brain CT scans and MRI, and employing state-of-the-art fusion techniques like landmark-based totally photo registration and wavelet remodel-primarily based fusion, the evolved Flask-based totally utility offers a holistic solution that enhances diagnostic accuracy and aids in medical choice-making. Moreover, the incorporation of convolutional neural network (CNN) fashions for automated tumor detection and classification represents a significant soar forward, simplifying evaluation approaches and elevating performance standards. Consequently, these improvements no longer best refine diagnostic precision however additionally hold the promise of placing new benchmarks for medical results, thereby positively impacting affected person care. Looking to the destiny, sustained exploration and refinement of multimodal fusion strategies are vital for advancing clinical imaging practices and unlocking in addition innovations. By always pushing the boundaries of generation and collaboration, we can aspire to redefine diagnostic standards, ultimately leading to progressed healthcare consequences and better patient experiences.

FUTURE ENHANCEMENTS AND DISCUSSIONS

In terms of future improvements and discussions, several avenues provide the capability for advances in clinical imaging and diagnostics, specifically inside the detection of mind tumors. First, exploring the integration of superior imaging methods including positron emission tomography (PET) or functional MRI (fMRI) may want to provide extra insights for complete tumor characterization and treatment planning. Second, delving into greater state-of-the-art fusion strategies past existing strategies, including landmark-based registration and wavelet transforms, can yield even greater robust integration of multimodal information, thereby growing diagnostic accuracy and reliability. Moreover, the continuous refinement and exploration of deep getting to know architectures, together with new processes along with transformer-based models, keep promise for enhancing the performance of computerized tumor detection and class. In addition, conducting massive-scale medical trials to affirm the effectiveness and reliability of developed packages in a actual-world healthcare setting is essential for their significant adoption and integration into habitual medical exercise.