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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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.

Internal Guide Head of the Department

Project coordinator External Examiner



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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ACKNOWLEDGEMENT

The satisfaction and euphoria that accompany the successful completion of any task would be incomplete without the mention of people who made it possible, whose constant guidance and encouragement crowned our efforts with success. It is a pleasant aspect that we now have the opportunity to express our guidance for all of them.

First of all, we would like to express our deep gratitude towards our internal guide **Dr. K Sai Prasad,** Associate Professor and HOD, Dept. of CSE-AIML for his support in the completion of our dissertation. We wish to express our sincere thanks to principal **Dr. K. SRINIVAS RAO** for providing the facilities to complete the dissertation.

We would like to thank all our faculty and friends for their help and constructive criticism during the project period. Finally, we are very much indebted to our parents for their moral support and encouragement to achieve goals.

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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 subtype. 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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APPENDIX-3 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 REFERENCES

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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 | N. Zsoter et al., "PET-CT ba | ased automated lung nodule detection," | |
| format | 2012 Annual International C | Conference of the IEEE Engineering in | |
| | Medicine and Biology Soci | ety, San Diego, CA, USA, 2012, pp. | |
| | 4974-4977, Doi: 10.1109/EMBC.2012.6347109. | | |
| | | | |
| URL of the Reference | Authors Names and | Keywords in this Reference | |
| URL of the Reference | Authors Names and Emails | Keywords in this Reference | |
| PET-CT based | | Keywords in this Reference PET-CT, lung nodule detection, | |
| | Emails | · | |

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

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

Major Impact Factors in this Work

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

| background mean | the region of nodules | detection and the | segmentation helps |
|---------------------|-----------------------|-----------------------|------------------------|
| ratio and the | properly in PET-CT | final classification | to build the basis for |
| subsequent steps in | studies. | step, particularly in | this classification. |
| the algorithm. | | cases where nearby | These variables |
| | | and similar nodules | mediate the |
| | | are merged into one. | 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 So | olution | Contr | | & The V | alue |
|------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------|--------------------------|----------------|-------------------------------------------------------|---------------------------------------|----------|---------------------------------|
| | | | | | | of This | s Work | |
| Input | Output | The use of | multiple | e fuzzy | This | work | develops | an |
| 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 | based tists segmentation automatically lungs inside which can be accuracy of detection. | detection of CT elp impr | ct the images, | nodule images, efficien physicia potentia | detection, improvency, as an ally imp | | Γ-CT aracy, ucing aload, atient |
| | the PET-CT image. | | | | | | | |
| Positive Impact of this Solution in This Project Domain | | Neg | | pact of the | | tion in Tl | nis | |

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.

| 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 | Analyse This Work by Critical Thinking | The Tools That Assessed this Work | What is the Structure of this Paper | | | |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------|--|--|--|
| Diagram/Flowchart | automated method for detecting lung nodules in PET-CT images, improving | evaluation software and various mathematical and image analysis methods such as fuzzy connectedness, morphological dilation, and multiple fuzzy-based tissue/organ segmentation | I. IntroductionII. Materials and methodsIII. ResultsIV. Conclusion and future | | | |
| | Diagram/Flowchart | | | | | |

---End of Paper 1---

| 2 | | | |
|------------------|-----------------------------------------------------------------|--|--|
| Reference in APA | C. Hima Bindu and K. Veera Swamy, "Medical image fusion using | | |
| format | 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 | Keywords in this Reference |
|----------------------------|------------------------------|----------------------------------------|
| | Emails | |
| https://ieeexplore.ieee.or | Ch. Hima Bindu, K. Veera | Image segmentation, Biomedical |
| g/document/6909206 | Swamy | imaging, PSNR, Computers, |
| | | Magnetic resonance imaging |
| The Name of the | The Goal (Objective) of | What are the components of it? |
| Current Solution | this Solution & What is | |
| (Technique/ Method/ | the problem that needs | |
| Scheme/ Algorithm/ | to be solved | |
| Model/ Tool/ | | |
| Framework/ etc) | | |
| Medical Image Fusion | The goal of this solution is | The proposed solution consists of a |
| using Content Based | to achieve less complex | multi-modal convolutional neural |
| Automatic Segmentation | fusion and improve the | network approach for medical |
| | performance of image | image segmentation, which includes |
| | fusion methods compared | three schemes for fusing |
| | to existing methods. The | information from different image |
| | problem that needs to be | modalities: fusing at feature level, |
| | solved is the limitations of | fusing at classifier level, and fusing |
| | pixel level image fusion | at decision level. |
| | methods such as sensitivity | |
| | to noise, blurring effects, | |
| | and miss registration. | |
| The Process (Macha | nism) of this Work. Magne 1 | How the Problem has Solved & |

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

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

| segmentation, | scheme used for | potential | medical image |
|----------------------|----------------------|---------------------|----------------------|
| measured by the | medical image | confounding factors | |
| Dice similarity | segmentation, which | and provide a | than examining the |
| coefficient (DSC) | includes three | comprehensive | underlying |
| and the Hausdorff | different fusion | assessment of the | mechanisms or |
| distance (HD), | architectures: early | segmentation | processes that may |
| which reflect the | fusion, late fusion, | accuracy. | mediate the |
| overlap and distance | and hybrid fusion. | , | relationship between |
| between predicted | | | the input images and |
| and ground truth | combine the | | the segmentation |
| segmentation masks, | information from | | output. |
| respectively. | MRI, CT, and PET | | 1 |
| | images at different | | |
| | stages of the deep | | |
| | learning pipeline to | | |
| | optimize the | | |
| | accuracy and | | |
| | robustness of the | | |
| | segmentation | | |
| | algorithm. | | |
| | | | |

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 |
|---------------|-------------|
| The input of | The output |
| this paper is | is a |
| the use of | generalized |
| deep | framework |
| learning to | of image |
| optimize the | fusion for |
| multi-modal | supervised |
| image | learning in |
| fusion | biomedical |
| architecture | image |
| for medical | |
| image | |
| segmentatio | |
| n for MRI, | |
| CT, and | |
| PET | |
| images. | |

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 improved accuracy robustness of medical image segmentation.

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 stateof-the-art in medical image analysis by providing 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.

Positive 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.

Negative Impact of this Solution in This Project Domain

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 | CT -MRl and MRl-PET | I. Introduction |
| noteworthy aspects of the | | II. Image Fusion |

| work. The study presents an | | III. | Proposed Method |
|-------------------------------|-------------------|----------|-----------------|
| innovative approach to | | IV. | Experimental |
| multi-modal medical image | | | Results |
| segmentation, but its limited | | V. | Conclusion |
| scope and lack of | | | |
| comprehensive comparative | | | |
| analysis may restrict the | | | |
| generalizability of the | | | |
| proposed image fusion | | | |
| schemes. | | | |
| | Diagram/Flowchart | | |
| | | | |
| C | | 1 | |
| | | | |
| Vo. | - A-3 | | |

---End of Paper 2---

| 3 | | | | |
|--------------|----------------|----------------------------------------------------------------|---------------------------------------|--|
| Referer | nce in APA | Himanshi, V. Bhateja, A. Krishn and A. Sahu, "An improved | | |
| fo | rmat | 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 | he Reference | Authors Names and | Keywords in this Reference | |
| | | | | |
| | | Emails | | |
| https://ieee | explore.ieee.o | Emails Himanshi, Vikrant Bhateja, | CT-Scan, DTCWT, Entropy, MRI | |
| | explore.ieee.o | | CT-Scan, DTCWT, Entropy, MRI and PCA. | |

| The Name of the | The Goal (Objective) of | What are the components of it? |
|-------------------------|----------------------------|--------------------------------|
| Current Solution | this Solution & What is | |
| (Technique/ Method/ | the problem that need to | |
| Scheme/ Algorithm/ | be solved | |
| Model/ Tool/ | | |
| Framework/ etc) | | |
| Improved medical | Goal is to combine MR and | Gray scale conversion, DTCWT |
| image fusion approach | CT-scan images to create a | decomposition, PCA and image |
| using PCA and Complex | single image that contains | fusion. |
| Wavelets. | 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. | |

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 | Simplifies the image | May result in some loss of |
| | CT-scan images from RGB | processing by reducing the | information, particularly |
| | scale to Gray scale to ensure | dimensionality of the | if the original images |
| | that the images have the | images. | contain important color |
| | same color space and can be | | information |
| | processed together. | | |

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

Major Impact Factors in this Work

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

| image | obtained | constitutes | the | methods | serve | as | enhancem | ent |
|-------------|-----------|----------------|----------|------------|-------|----|-------------|-------------|
| through the | proposed | independent va | ıriable. | moderatin | g | | property of | of PCA, act |
| PCA and I | Dual Tree | | | variables. | | | as | mediating |
| Complex | Wavelet | | | | | | variables. | |
| (DTCWT) | fusion | | | | | | | |
| approach. | | | | | | | | |

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.

Feature of This Solution

Contribution & The Value

Input and Output

medical diagnoses.

| | | 1 04041 0 01 | | of This Work | |
|---------------------------------------------|------------------|------------------------------------------------------------|---------------------------------|-------------------------------------------------------------------------------------------------------------------------|--|
| | | The use of DTCWT and PCA | | Contribution and the value of | |
| Input Output | | helps to improve the visual quality of the fused image and | | this work lies in the proposed improved fusion approach for | |
| MR and CT- scan images | A fused image | increase the effectiveness of the fusion process. | | medical images using PCA and DTCWT. The approach | |
| images | | | | demonstrates an improvement in visual quality of the fused image supported by higher values of fusion metrics. | |
| Positive Impa | act of this Solu | ition in This | Negative Im | pact of this Solution in This | |
| Pı | roject Domain | 1 |] | Project Domain | |
| The proposed | approach enl | nances visual | Challenges such | as the computational intensity | |
| quality, increases fusion process | | of DTCWT, po | tentially increasing processing | | |
| effectiveness with DTCWT and PCA, and | | | time and cost, a | and the risk of information loss | |
| improves efficiency through PCA-based | | | during fusion, ir | npacting diagnosis accuracy. | |
| fusion rules, contributing to more accurate | | | | | |

| Analyse This Work By Critical Thinking | The Tools That Assessed this Work | What is the Structure of this | | | | | |
|-------------------------------------------------------------------------------------------------------|-----------------------------------|-------------------------------|--|--|--|--|--|
| Critical Thinking | tills vvork | Paper | | | | | |
| This approach combines | Entropy (E) and Fusion | Abstract | | | | | |
| DTCWT and PCA, showing | Factor (FF) are used as fusion | I. Introduction | | | | | |
| promise for enhanced visual | metrics. | II. Proposed Fusion | | | | | |
| quality and effectiveness in | | Approach | | | | | |
| medical image fusion. | | III. Experimental | | | | | |
| However, computational | | Results and | | | | | |
| complexity and possible | | Discussions | | | | | |
| information loss are | | IV. Conclusion | | | | | |
| limitations, requiring further | | | | | | | |
| research for validation and | | | | | | | |
| addressing these challenges. | | | | | | | |
| Diagram/Flowchart | | | | | | | |
| Quality Evaluation of Fused Image (IDTCWT) Preprocessing Decomposition using DTCWT PCA Fusion Rule | | | | | | | |
| End of Donor 2 | | | | | | | |

--End of Paper 3—

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

| https://ieeexplore.ieee.or | Zhe Guo, Xiang Li | medical image segmentation, |
|----------------------------|----------------------------|---------------------------------------|
| g/document/8363717 | | biomedical imaging, medical |
| | | applications, lesion segmentation, |
| | | multimodality images |
| The Name of the | The Goal (Objective) of | What are the components of it? |
| Current Solution | this Solution & What is | - |
| (Technique/ Method/ | the problem that needs to | |
| Scheme/ Algorithm/ | be solved | |
| Model/ Tool/ | | |
| Framework/ etc) | | |
| , | | |
| Medical image | This solution aims to | The proposed solution consists of a |
| segmentation based on | propose a generalized | multi-modal convolutional neural |
| multi-modal | framework of image fusion | network approach for medical image |
| convolutional neural | for supervised learning in | segmentation, which includes three |
| network: study on image | biomedical image analysis | schemes for fusing information from |
| fusion schemes | and implement the fusion | different image modalities: fusing at |
| | schemes based on deep | feature level, fusing at classifier |
| | convolutional neural | level, and fusing at decision level. |
| | 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 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 | it provides a unified | it may not be suitable for | |
| | fusion schemes, including | framework for multi-modal | all scenarios, and some | |
| | fusing at feature level, | image processing, which | modifications may be | |
| | fusing at classifier level, and | can guide the methodology | necessary. | |
| | fusing at decision level. | design for various | | |
| | | applications. | | |
| 2 | Preprocessing of the multi- | it can improve the quality | it may introduce bias or | |
| | modal soft tissue sarcoma | of the input data and reduce | errors if not done | |
| | imaging dataset. | noise and artifacts. | carefully. | |
| 3 Training and testing of the | | it can optimize the model | it requires a large amount | |
| | three image segmentation | parameters and improve the | of labeled data and | |
| | models based on the | accuracy and robustness of | computational resources. | |
| | Convolutional Neural | the segmentation. | | |
| | Network (CNN) structure. | | | |
| 4 | Evaluation of the | it can provide insights into | it may not be able to | |
| | performance difference | the performance difference | capture all aspects of the | |
| | across different fusion | across different fusion | problem and may require | |
| | schemes and the cause. | schemes and the cause | further investigation. | |
| | | thereof. | | |
| | | | | |

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 | Dependent Variable Independent | | Mediating |
|---------------------------|--------------------------------|------------------------|-----------------------|
| | Variable | variable | (Intervening) |
| | | | variable |
| The dependent | The independent | it does use cross- | The study focuses on |
| variable in this study | variable in this paper | validation and | optimizing the multi- |
| is the accuracy of | is the type of multi- | multiple evaluation | modal image fusion |
| medical image | modal image fusion | metrics to control for | architecture for |
| segmentation, | scheme used for | potential | medical image |
| measured by the Dice | medical image | confounding factors | segmentation, rather |
| similarity coefficient | segmentation, which | and provide a | than examining the |
| (DSC) and the | includes three | comprehensive | underlying |
| Hausdorff distance | different fusion | assessment of the | mechanisms or |
| (HD), which reflect | architectures: early | segmentation | processes that may |
| the overlap and | fusion, late fusion, | accuracy. | mediate the |
| distance between | and hybrid fusion. | | relationship between |
| predicted and ground | These architectures | | the input images and |
| truth segmentation | combine the | | the segmentation |
| masks, respectively. | information from | | output. |
| | MRI, CT, and PET | | |
| | images at different | | |
| | stages of the deep | | |
| | learning pipeline to | | |
| | optimize the | | |
| | accuracy and | | |
| | robustness of the | | |
| | segmentation | | |
| | algorithm. | | |
| Dalati | onship Among the Aho | 4 V | 4-1- |

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 | | | This Solution | Contribution & The Value |
|--------------------------|----------|----------------|--------------------|-----------------------------------|
| input and Output | | r cature or | This Solution | of This Work |
| | | | | |
| | | solution feat | ures the use of | Our work contributes a novel |
| Input Ou | tput | multi-modal | image fusion, a | multi-modal image fusion |
| TDI : 4 C TDI | | novel cond | ceptual image | architecture for medical image |
| | 1 | fusion archite | ecture, the use of | segmentation using |
| this paper is is | a | Convolutiona | ıl Neural | Convolutional Neural |
| the use of genera | | Networks (C | CNNs), and the | Networks (CNNs), which has |
| deep frame | work | evaluation of | of performance | the potential to improve the |
| learning to of | image | differences | across different | accuracy and robustness of |
| optimize the fusion | n for | fusion sch | nemes. These | medical image segmentation. |
| multi-modal superv | vised | features | contribute to | This work advances the state- |
| image learni | ng in | | accuracy and | of-the-art in medical image |
| fusion biome | edical | • | f medical image | analysis by providing a |
| architecture image | • | segmentation | • | comprehensive evaluation of |
| for medical | | segmentation | • | different fusion schemes and |
| image | | | | |
| segmentatio | | | | their impact on segmentation |
| n for MRI, | | | | performance, and by providing |
| CT, and PET | | | | insights into the characteristics |
| images. | | | | of the feature learning and |
| mages. | | | | impact of errors on the |
| | | | | learning process. |
| Positive Impact of t | his Solu | tion in This | Negative Imp | pact of this Solution in This |
| Project 1 | Domain | | l | Project Domain |
| The proposed multi- | modal i | image fusion | The feature-leve | el fusion scheme in the proposed |
| architecture for | medic | _ | | ation 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 | The Tools That Assessed | What is the Structure of |
|-------------------------------|--------------------------------------------------------------------------------------------------|--------------------------|
| | | |
| Critical Thinking | this Work | this Paper |
| The analysis reveals | TensorFlow, Open CV, | I. abstract |
| noteworthy aspects of the | Dataset, Matplotlib | II. Introduction |
| work. The study presents an | | III. Related Work |
| innovative approach to multi- | | IV. Experiments |
| modal medical image | | V. Conclusion |
| segmentation, but its limited | | |
| scope and lack of | | |
| comprehensive comparative | | |
| analysis may restrict the | | |
| generalizability of the | | |
| proposed image fusion | | |
| schemes. | | |
| | Diagram/Flowchart | |
| | | |
| PET | | _ |
| ст | 2×2×3 2×2 3×2 2×2 2×2 2×2 2×2 2×2 2×2 2× | Soft-10 |
| TZ- MR | | (a) |
| PET | 2×2 2×2 2×2 2×3 Avg conv conv conv conv Pool 16 36 64 144 23 | _ |
| ст | 2×2 2×2 2×2 2×2 2×2 2×2 4×3 FC FC FC 200V 16 864 23 FG FC 200V 200V 200V 200V 200V 200V 200V 200 | max 1 |
| T2- MR | 2×2 2×2 2×2 2×2 4×g conv conv conv conv loo 144 23 | (b) |
| PET | 2=2x3 | |
| ст | 2×2x3 2×2 2×2 2×2 2×2 2×2 4×g Pool FC FC FC Suff ma. | |
| T2- MR | 2×2×3 2×2 2×2 2×2 4vg FC FC FC Soft senv Pool 964 298 2 ma | 10 d (c) |

---End of Paper 4---

5

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

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

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

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

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 |
|------------------|---------|-------------------------------|------------------------------|
| | | Utilizes Discrete Wavelet | Contribution lies in the |
| Input Output | | Transform (DWT) for image | experimental results of the |
| _ | | 1 | proposed method using DWT |
| PET and | A fused | fusion rule for combining | has demonstrated that the |
| MRI images | image | information from diverse | proposed method outperforms |
| of brain | | modalities, and incorporates | other existing techniques in |
| | | post-processing techniques to | terms of image quality and |

| | enhance the | fused image | preservati | on of important | |
|---------------------------------------------------------------------------|-------------------|-------------------|--------------|------------------------------------------|--|
| | quality. | | features. | 33. 33. 33. F 33. 33. 33. 33. 33. 33. 33 | |
| Positive Impact of this Solu | ition in This | Negative Imp | pact of this | s Solution in This | |
| Project Domain | 1 | 1 | Project Do | main | |
| It achieves high accuracy o | utcomes and | It may introduce | e some arti | facts and distortions | |
| preserves both the spectral an | d anatomical | in the processed | images. | | |
| data, making it a valuable too | ol for medical | | | | |
| image processing. | | | | | |
| Analyse This Work by | The Tools | That Assessed | What is t | he Structure of this | |
| Critical Thinking | this | Work | | Paper | |
| The proposed solution, | Root mean | square error | Abstract | | |
| using Discrete Wavelet | (RMSE), per | centage fit error | I. | Introduction | |
| Transform (DWT), | (PFE), signa | l to noise ratio | II. | Related Work | |
| significantly enhances | (SNR), pea | ak signal to | III. | Proposed Fusion | |
| medical image quality for | interference | ratio (PSNR), | | Approach | |
| clinical diagnosis, achieving | correlation c | oefficient (CC), | IV. | Experimental | |
| 90-95% more accuracy. | mutual info | ormation (MI), | | Analysis | |
| Tested on Alzheimer's and | universal | quality index | V. | Conclusion | |
| normal brain image | (UQI), struc | tural similarity | | | |
| datasets, DWT improves | index measur | re (SSIM) | | | |
| fused image quality, with | | | | | |
| effectiveness depending on | | | | | |
| specific datasets and | | | | | |
| performance measures. | | | | | |
| | Diagram/Flowchart | | | | |
| Diagram/Flowchart Source images Multiscale Fused Image MRI DWT DWT IDWT | | | | | |

--End of Paper 5--

| Reference in APA | K. Vanitha, D. Satyanarayana and M. N. G. Prasad, "Multimodal | | |
|----------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------|--|
| format | 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 Keywords in this Referen | | |
| | Emails | | |
| https://ieeexplore.ieee.o | K.Vanitha, | Multimodal medical image fusion, | |
| rg/document/8944896 | Dr.D.Satyanarayana and | hybrid 11-10 decomposition, base | |
| | Dr.M.N.Giri Prasad | layer, detail layer. | |
| The Name of the | The Goal (Objective) of | What are the components of it? | |
| Current Solution | this Solution & What is | | |
| (Technique/ Method/ | the problem that need to | | |
| Scheme/ Algorithm/ | be solved | | |
| Model/ Tool/ | | | |
| Framework/ etc) | | | |
| Multimodal medical | The seal of this are doing | 1. Hybrid 11-10 decomposition model | |
| | | | |
| limago tugion that | The goal of this work is to | _ | |
| image fusion that | develop a new method for | Weighted average fusion rule | |
| combines multiscale decomposition and | | _ | |
| combines multiscale | develop a new method for multimodal medical image | 2. Weighted average fusion rule | |
| combines multiscale decomposition and | develop a new method for multimodal medical image fusion that can provide a | 2. Weighted average fusion rule3. Average fusion rule4. Linear combination | |
| combines multiscale decomposition and hybrid 11-10 | develop a new method for multimodal medical image fusion that can provide a more complete and accurate | 2. Weighted average fusion rule3. Average fusion rule | |
| combines multiscale decomposition and hybrid 11-10 | develop a new method for multimodal medical image fusion that can provide a more complete and accurate representation of the | 2. Weighted average fusion rule3. Average fusion rule4. Linear combination | |
| combines multiscale decomposition and hybrid 11-10 | develop a new method for multimodal medical image fusion that can provide a more complete and accurate representation of the underlying anatomy or | 2. Weighted average fusion rule3. Average fusion rule4. Linear combination | |
| combines multiscale decomposition and hybrid 11-10 | develop a new method for multimodal medical image fusion that can provide a more complete and accurate representation of the underlying anatomy or pathology. | 2. Weighted average fusion rule3. Average fusion rule4. Linear combination | |
| combines multiscale decomposition and hybrid 11-10 | 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 | 2. Weighted average fusion rule3. Average fusion rule4. Linear combination | |
| combines multiscale decomposition and hybrid 11-10 | 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 | 2. Weighted average fusion rule3. Average fusion rule4. Linear combination | |

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 11-10 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 11-l0 decomposition | It can preserve edges and | It may not be suitable for |
| | model is used to decompose | contours while reducing | all types of images and |
| | the source images into base | noise and artifacts in the | may require careful |
| | and detail layers, which | image. | tuning of parameters. |
| | contain information about | | |
| | edges, boundaries, and | | |
| | contours. | | |
| 2 | Weighted average fusion | It can preserve fine details | It may also introduce |
| | rule is used to identify the | and textures in the image, | artifacts or noise if the |
| | detailed information in the | which may be important for | weights are not carefully |
| | source images and combine | accurate diagnosis or | chosen. |
| | it into a single fused image | treatment planning | |
| 3 | Average fusion rule is used | It can highlight edges, | It may also smooth out or |
| | to combine the base layers of | boundaries, and contours in | blur important details in |
| | the source images into a | the image, which may be | the image. |
| | single fused image. | important for visual | |
| | | interpretation. | |
| 4 | The final fused image is | It can balance the | it may also introduce |
| | obtained by combining the | contributions of the detail | artifacts or noise if the |
| | detail and base layers using | and base layers to obtain a | weights are not carefully |
| | a linear combination. | | chosen. |

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

| Dependent Independen | | Moderating | Mediating |
|-----------------------|-----------------------|-----------------------|----------------------|
| Variable | Variable | variable | (Intervening) |
| | | | variable |
| The effectiveness | The components of | Factors that moderate | The transfer of the |
| and performance of | the method, | the relationship | most important |
| the proposed two- | including the hybrid | between the | information from the |
| scale decomposition | L1-L0 | independent variable | source to the fused |
| based multimodal | decomposition | and the dependent | image acts as a |
| medical image fusion | model, the weighted | variable include the | mediating variable. |
| method, as measured | average fusion rule | reduction of | |
| by objective criteria | for detailed | information loss and | |
| serve as the | information, and the | fusion artifacts. | |
| dependent variable. | average fusion rule | | |
| | for base layers, | | |
| | constitute the | | |
| D.L.« | independent variable. | 4.87 | |

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 7 | This Solution | Contribution & The Value | |
|--------------------------------------------|-----------------|------------------------------|-------------------|-----------------------------------|--|
| | | | | of This Work | |
| | | The main f | eature of this | The contribution of this work | |
| Input | Output | solution is th | e use of hybrid | is the development of a novel | |
| _ | _ | 11-10 decomp | osition model to | method for multimodal | |
| CT and MRI | A fused . | decompose th | e source images | medical image fusion that | |
| images of | image | into base an | d detail layers, | combines several techniques to | |
| brain | | which conta | in information | obtain a more complete and | |
| | | about edges, | boundaries, and | accurate representation of the | |
| | | contours. The | detail layers are | underlying anatomy or | |
| | | then combi | ned using a | pathology. Additionally, the | |
| | | weighted ave | rage fusion rule, | objective evaluation criteria | |
| | | while the base layers are | | used in this work can help | |
| | | combined using an average | | researchers compare and | |
| | | fusion rule. The final fused | | benchmark different methods | |
| | | image is | obtained by | for medical image fusion, | |
| | | combining the | e detail and base | which can lead to further | |
| | | layers usir | ng a linear | improvements in the field. | |
| | | combination. | | | |
| Positive Impa | ct of this Solu | tion in This | Negative Im | pact of this Solution in This | |
| Pı | oject Domain | 1 | | Project Domain | |
| The proposed | multimodal m | edical image | Potential negat | ive impacts of the proposed | |
| fusion method | improves in | nage quality, | solution includ | e complexity due to multiple | |
| reduces noise and artifacts using a hybrid | | | steps and parar | neters requiring careful tuning, | |
| 11-10 decomposition model, and employs | | | sensitivity to | image characteristics, such as | |
| objective criteria for quantitative | | | modality and re | esolution, and a potentially high | |
| evaluation in the medical imaging. | | | computational c | cost for large or high-resolution | |
| | | | images, impac | cting practicality in certain | |
| | | | settings. | | |
| | | | 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 |
| I. | Base Images Fusion of Base images Hybrid Island Base images (x, y) Superposition Fusion rule Pusion of Detail images Fusion of Detail images | F U S E D I M A G E |

--End of Paper 6--

| 7 | | |
|-----------------------------|-----------------------------------------------------------------|--------------------------------------|
| Reference in APA | Jiaxin Li, Houjin Chen, Ya | nfeng Li, and Yahui Peng. 2019. A |
| format | Novel Network Based on De | ensely 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.or | rg/10.1145/3358331.3358400 |
| URL of the Reference | Authors Names and | Keywords in this Reference |
| | Emails | |

| https://dl.acm.org/doi/a | Jiaxin Li, Houjin Chen, | MR Image segmentation; lung |
|------------------------------|------------------------------|------------------------------------|
| <u>bs/10.1145/3358331.33</u> | Yanfeng Li and Yahui Peng | tumour segmentation; multi-modal |
| <u>58400</u> | | fusion; fully convolutional |
| | | networks; Hyper-DenseNet |
| The Name of the | The Goal (Objective) of | What are the components of it? |
| Current Solution | this Solution & What is | |
| (Technique/ Method/ | the problem that need to | |
| Scheme/ Algorithm/ | be solved | |
| Model/ Tool/ | | |
| Framework/ etc) | | |
| A Novel Network Based | The goal is to improve the | A densely connected fully |
| on Densely Connected | accuracy of lung tumor | convolutional network and a hyper- |
| Fully Convolutional | segmentation on multi- | densely connected CNN model for |
| Networks for | modal MR images, which is | multi-modality fusion |
| Segmentation of Lung | important for the benign | |
| Tumors on Multi-Modal | and malignant | |
| MR Images | 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. | |

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 | | A | dvantage | | Disadvant | age |
|---|-----------------------------|--------------|-------------|--------------------|---------|-------------|-----------|
| | | | | | | (Limitatio | on) |
| 1 | The preprocessin | g of data by | Ensures | data consistency | Potent | tial los | ss of |
| | selecting slices a | at the same | for deep | learning model | inforn | nation if i | mportant |
| | location for both | modalities | training. | | slices | are exclude | ed during |
| | and resizing the | images to a | | | resizir | ng. | |
| | consistent resolu | tion. | | | | | |
| 2 | A novel | network | The nov | vel architecture | Comp | lexity | and |
| | architecture is u | used which | accurately | segments lung | interp | retability | |
| | combines a | densely | tumors, a | chieving state-of- | challe | nges; si | gnificant |
| | connected | fully | the-art per | formance. | compi | utational | resources |
| | convolutional ne | twork and a | | | may b | e required. | |
| | hyper-densely | connected | | | | | |
| | CNN model | for multi- | | | | | |
| | modality fusion. | | | | | | |
| 3 | The network is tr | ained using | Binary c | ross-entropy and | Potent | tial diffic | culty in |
| | a combination of binary | | Dice loss | combination aids | tuning | g hyperpa | rameters, |
| | cross-entropy los | ss and Dice | in effectiv | e training. | especi | ially ł | alancing |
| | loss. | | | | betwe | en the t | wo loss |
| | | | | | functi | ons. | |
| 4 | Dice Similarity | Coefficient | DSC is | a widely used | Limite | ed in capt | uring all |
| | (DSC) to qu | antitatively | metric, | providing a | aspect | ts of segn | nentation |
| | evaluate the performance of | | quantitati | ve measure of | perfor | mance; | |
| | the network. | | segmentat | ion accuracy. | compa | arability | across |
| | | | | | datase | ets mag | y be |
| | | | | | challe | nging. | |
| | | Major I | mpact Fac | tors in this Work | | | |
| | Dependent | Indepe | ndent | Moderating | | Media | ting |
| | Variable | Varia | ble | variable | | (Interve | ning) |
| | | | | | | varia | ble |
| | | | | | | | |

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

Relationship Among the Above 4 Variables in This article

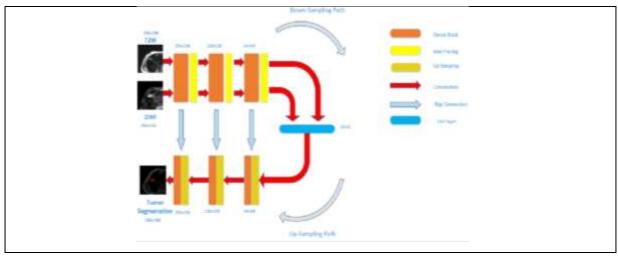
The independent variables that include multi-modal fusion and network architectures impact lung tumor segmentation accuracy, assessed through comparison to single-modal methods. The effectiveness of the fusion and architecture combination is crucial, emphasizing the proposed method's design in achieving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

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

Positive Impact of this Solution in This Negative Impact of this Solution in This Project Domain Project Domain The method enhances accuracy and The method's practical application might be efficiency in lung tumor segmentation, a hindered in certain settings due to its potential crucial step in lung cancer diagnosis and for increased computational demands and longer treatment, with potential applicability to processing times other medical image analysis tasks, improving treatment planning and patient outcomes. **Analyse This Work By** The Tools That Assessed What is the Structure of this this Work **Critical Thinking Paper** The method Use of Dice Similarity Abstract proposed combines Coefficient fully (DSC) as I. Introduction convolutional and hyperquantitative evaluation II. Methodology densely connected CNN metric to measure the III. **Experiments** models for automated lung performance of the proposed IV. Conclusions tumor segmentation on MR network. images. However, limitations include the need computational for more resources, longer processing time, and etc. Overall, it contributes significantly to medical image analysis and enhancing lung tumor segmentation's accuracy

Diagram/Flowchart

and efficiency.



--End of Paper 7--

| (| (| | þ | | |
|---|---|---|---|---|--|
| i | ľ | ١ | ١ | ı | |

| 8 | | | | | |
|-------------------------|-------------------------------------------------------------|---------------------------------------|--|--|--|
| Reference in APA | K. S. Asish Reddy, K. Kalyan Kumar, K. N. Kumar, V. Bhavana | | | | |
| format | and H. K. Krishnappa, "I | Multimodal Medical Image Fusion | | | |
| | Enhancement Technique f | for Clinical Diagnosis," 2019 3rd | | | |
| | International Conference | on Computing Methodologies and | | | |
| | Communication (ICCMC), l | Erode, India, 2019, pp. 586-589, Doi: | | | |
| | 10.1109/ICCMC.2019.8819 | 840. | | | |
| URL of the Reference | Authors Names and | Keywords in this Reference | | | |
| | Emails | | | | |
| Multimodal Medical | K Sai Asish Reddy, K | Discrete Wavelet Transform | | | |
| <u>Image</u> Fusion | Kalyan Kumar, K Naveen | (DWT), Image Fusion, Principal | | | |
| Enhancement | Kumar, Bhavana V, | Component Analysis (PCA) | | | |
| Technique for Clinical | Krishnappa H. K | | | | |
| Diagnosis IEEE | | | | | |
| Conference Publication | | | | | |
| IEEE Xplore | | | | | |
| The Name of the | The Goal (Objective) of | What are the components of it? | | | |
| Current Solution | this Solution & What is | | | | |
| (Technique/ Method/ | the problem that need to | | | | |
| Scheme/ Algorithm/ | be solved | | | | |

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

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

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

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

| | 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 | This work presents a solution |
| Medical | A single | multiple medical images | for improving clinical |
| images from | fused image | | diagnosis accuracy, reducing |
| different | that | a single image, providing | data requirements, being |
| modalities | provides | accurate, informative data for | reliable, applicable to multiple |
| such as | more | clinical diagnosis using | imaging modalities, and |
| PET, MRI | comprehens | advanced algorithms like | potentially gaining wider |
| and CT. | ive and | DWT and PCA. | adoption, ultimately leading to |
| | reliable data | | improved patient outcomes |
| | for clinical | | and improved healthcare |
| | diagnosis. | | delivery. |

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

| Analyse This Work By | The Tools That Assessed | What is the Structure of this | | | |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|--|--|--|
| Critical Thinking | this Work | 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 | | | | |
| MRI Fusion rule DWT DWT CT/PET image | CT/PET image Fused image (F) MRI image | Principle component analysis Fused image | | | |

---End of Paper 8---

| 9 | | |
|-----------------------------|-----------------------------------------------------------|-----------------------------------|
| Reference in APA | H. Yan and Z. Li, "A Multi-1 | modal Medical Image Fusion Method |
| format | in Spatial Domain," 2019 IEEE 3rd Information Technology, | |
| | Networking, Electronic an | d Automation Control Conference |
| | (ITNEC), Chengdu, Chi | ina, 2019, pp. 597-601, doi: |
| | 10.1109/ITNEC.2019.87291 | 43. |
| | | |
| URL of the Reference | Authors Names and | Keywords in this Reference |
| | Emails | |
| | | |

| https://ieeexplore.ieee.or | Huibin Yan and Zhongmin | Multi-modal medical image fusion; |
|----------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| g/document/8729143 | Li | spatial domain; moving frame- |
| | | based decomposition framework; |
| | | weight map |
| The Name of the | The Goal (Objective) of | What are the components of it? |
| Current Solution | this Solution & What is | • |
| (Technique/ Method/ | the problem that need to | |
| Scheme/ Algorithm/ | be solved | |
| Model/ Tool/ | | |
| Framework/ etc) | | |
| A multi-modal medical | The goal of the proposed | 1. Moving Frame Based |
| image fusion method | solution in this paper is to | Decomposition Framework |
| based on multi-scale | develop a fast and efficient | (MFDF) for decomposing the input |
| transform (MST). | 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 | 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. |
| | applications | |

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

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

Relationship Among the Above 4 Variables in This article

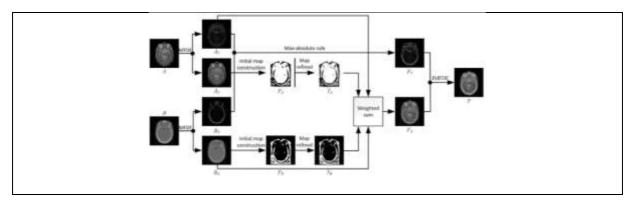
The components of the proposed method (independent variable) affect image fusion quality, with this relationship influenced by mediating processes (decomposition and weight map strategy) and moderated by external factors (input image characteristics, imaging modalities, and medical scenario complexity).

| Input and | d Output | Feature of This Solution | Contribution & The Value |
|----------------------|----------|---------------------------------|--------------------------------|
| | | | of This Work |
| | | It achieves a quick and | |
| Input | Output | efficient image fusion via | proposes a rapid and efficient |
| _ | _ | single-level decomposition, | multi-modal medical image |
| A set of multi-modal | A fused | surpassing methods with | fusion method, enhancing |
| illuiti-illodai | image | multiple levels. By utilizing a | contrast and preserving edge |
| | | Moving Frame Based | and texture information |

| medical | Decomposition Framework, through a novel weight | map |
|------------------------|----------------------------------------------------------|--------|
| images | it effectively preserves edge refined strategy. This | work |
| | and texture information, has the potential to im- | prove |
| | yielding high-contrast medical image f | usion |
| | images that closely align accuracy and effici | ency, |
| | with human vision, crucial offering valuable applica | ations |
| | for clinical applications. in disease diagnosis, treat | tment |
| | planning. | |
| Positive Impact of the | s Solution in This Negative Impact of this Solution in T | hic |

| Negative Impact of this Solution in This |
|-----------------------------------------------|
| Project Domain |
| Absence of comparative analysis with existing |
| methods are notable weaknesses |
| |
| |
| |
| |
| |

| Analyse This Work By | The Tools That Assessed | What is the Structure of |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------|
| Critical Thinking | this Work | this Paper |
| 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. | 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- | I. Introduction II. Several Basic Theories III. The Proposed Fusion Method IV. Experiments and Discussion V. Conclusion |
| | the-art methods. Diagram/Flowchart | |



---End of Paper 9--

| 10 | | | |
|-------------------------|--------------------------------------------------------------|----------------------------------|--|
| Reference in APA | V. A. Rani and S. Lalitha Kumari, "A Hybrid Fusion Model for | | |
| format | Brain Tumor Images of MRI and CT," 2020 International | | |
| | Conference on Communication and Signal Processing (ICCSP), | | |
| | Chennai, India, 202 | 20, pp. 1312-1316, Doi: | |
| | 10.1109/ICCSP48568.2020.9 | 9182371. | |
| URL of the Reference | Authors Names and | Keywords in this Reference | |
| | Emails | | |
| A Hybrid Fusion Model | V. Amala Rani and S. | CT, image fusion, MRI, discrete | |
| for Brain Tumor Images | Lalitha Kumari | wavelet transforms | |
| of MRI and CT IEEE | | | |
| Conference Publication | | | |
| IEEE Xplore | | | |
| The Name of the | The Goal (Objective) of | What are the components of it? | |
| Current Solution | this Solution & What is | | |
| (Technique/ Method/ | the problem that need to | | |
| Scheme/ Algorithm/ | be solved | | |
| Model/ Tool/ | | | |
| Framework/ etc) | | | |
| A Hybrid Fusion Model | Goal: Develop a hybrid | The proposed hybrid image fusion | |
| for Brain Tumor Images | image fusion technique that | algorithm consists of two main | |
| of MRI and CT | can effectively combine the | components: Empirical mode | |
| | MRI and CT images of | | |

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

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

| Dependent | Independent | Moderating | Mediating |
|-------------------------|-----------------------|------------------------|------------------------|
| Variable | Variable | variable | (Intervening) |
| | | | variable |
| Fused image quality: | Empirical Mode | Hybrid Fusion | Spatial |
| It reflects the overall | Decomposition | Response: It | Characteristics of the |
| quality of the fused | (EMD) of images | represents the overall | Original Image: The |
| image obtained | and discrete wavelet | outcome of the | method claims to |
| through the EMD | transform (DWT) | proposed approach as | retain the spatial |
| and DWT-based | method: It represents | it moderates the | characteristics of the |
| fusion method. | the methods used for | contribution of both | original image in the |
| | multimodal image | EMD and DWT in | fused result, |
| | fusion. | the image fusion | indicating a |
| | | process. | 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.

| Input and Output | | Feature of 7 | This Solution | Contribution in This Work |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------|--------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Input MRI and CT images of the brain. | Output A fused image and various performance metrics that evaluate quality and information content of fused image. | functional information CT images enhancing acc hybrid fusion on empi | n and discrete | 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. |
| _ | nct of this Solu | | | pact of this Solution in This Project Domain |
| AI-powered medical imaging er diagnosis accuracy, reduces manual and improves image quality across revolutionizing healthcare t efficient and reliable disease detect treatment. | | nanual errors, cross organs, e through | imaging tasks of and task contex for validation addressing com | 's effectiveness in medical lepends on input image quality t, necessitating further research across diverse datasets and aplex computational steps and nentation challenges. |
| | | | That Assessed Work | What is the Structure of this Paper |
| The hybrid employing EM for multimodal fusion enhance but faces chall | I brain image ces accuracy | (RMSE), Po Noise Ra Entropy, Star | Square Error eak Signal to atio (PSNR), and and Deviation al Information | Abstract I. Introduction II. Related Works III. Proposed Work |

| | | ~ 1 | | |
|------------------------------|----------------------------------------|-------------|--------------|----------------|
| to input quality sensitivity | (MI), and | Structural | IV. | Experiment |
| and computational | Similarity (SSIM) | | | Results and |
| complexity, requiring | | | | Discussions |
| further validation for real- | | | V. | Conclusion |
| world applicability. | | | | |
| | Diagram/Flo | wchart | | |
| | | | | |
| CT → EMD → | DWT Low freq coeffs High freq coeffs | Fusion | Fused coeffs | |
| MRI → EMD → | DWT Low freq coeffs High freq coeffs | Fusion Rule | | IDWT ded Image |

---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. <i>J Ambient Intell Human Comput</i> 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 | |
| | Emans | | |
| https://link.springer.com /article/10.1007/s12652- 020-02386-0#citeas | Manjit Kaur & Dilbag Singh | Fusion, Diagnosis, CNN, Multi-modality, Differential evolution. | |

| (Technique/ Method/ | the problem that need to | |
|------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------|
| Scheme/ Algorithm/ | be solved | |
| Model/ Tool/ | | |
| Framework/ etc) | | |
| Multi-modality medical | Goal: To fuse multi- | The proposed approach combines |
| image fusion technique | modality medical images to | non-subsampled contourlet |
| using multi-objective | obtain a more informative | transform (NSCT) decomposition, |
| differential evolution | and accurate representation | Xception-based feature extraction, |
| based deep neural | of the underlying anatomy | multi-objective differential evolution |
| networks. | or pathology. | for feature selection, and coefficient |
| | 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. | of determination and energy loss- based fusion functions to construct superior multi-modality medical images compared to competitive methods. |

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

| 2 | Feature extraction using an | The Inception architecture | The use of a deep neural |
|---|------------------------------|-----------------------------|----------------------------|
| | | • | _ |
| | extreme version of the | is a state-of-the-art deep | network for feature |
| | Inception neural network | neural network that has | extraction may require |
| | architecture. | been shown to be effective | significant computational |
| | | in various computer vision | resources and may be |
| | | tasks, including feature | sensitive to the choice of |
| | | extraction from medical | hyper-parameters. |
| | | images. | |
| 3 | Feature selection using a | The multi-objective | The feature selection step |
| | multi-objective differential | differential evolution | may require extensive |
| | evolution algorithm. | algorithm is a powerful | hyper-parameter tuning |
| | | optimization technique that | and may be sensitive to |
| | | can help to select the most | the choice of optimization |
| | | informative features from | algorithm. |
| | | the input images, which can | |
| | | improve the accuracy and | |
| | | efficiency of the overall | |
| | | approach. | |
| 4 | F 1 (C'' ' | | |
| 4 | Fused coefficient | The use of coefficient of | |
| | computation using | determination and energy | functions may affect the |
| | coefficient of determination | | |
| | and energy loss based fusion | can help to combine the | approach and may require |
| | functions. | most informative features | extensive experimentation |
| | | from the input images and | and validation. |
| | | obtain a more accurate and | |
| | | informative representation | |
| | | of the underlying anatomy | |
| | | or pathology. | |
| 5 | Fused image computation | The inverse non- | The inverse non- |
| | using the inverse non- | subsampled contourlet | subsampled contourlet |
| | subsampled contourlet | transform can help to | transform may be |
| | transform. | reconstruct the fused image | computationally complex |

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

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

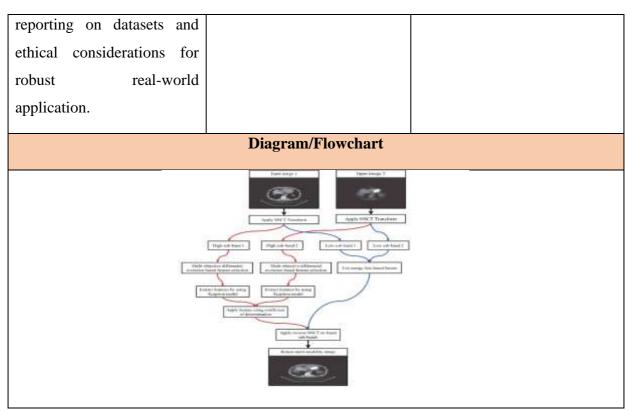
Relationship Among The Above 4 Variables in This article

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 |

| | | The propose | d solution is a | A multi-objective differential |
|--------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------|--------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Input | Output | multi-modalit | ty medical | evolution and Xception model |
| medical images | multi- modality medical images | combines | deep neural do optimization to obtain and accurate and of the anatomy or | 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 |
| Positive Impact of this Solution in This Project Domain | | | Negative Im | pact of this Solution in This |
| | | |] | Project Domain |
| The positive is | mpact of this valical profession and decisions are | work is that it nals to make | The use of techniques, espe | advanced image processing cially in the medical field, raises patient privacy and data security, |
| The positive is can help med more informed patient outcomes | dical profession ed decisions | vork is that it nals to make and improve | The use of techniques, especoncerns about prequiring care | advanced image processing cially in the medical field, raises patient privacy and data security, |
| The positive is can help med more informed patient outcomes | dical profession and decisions and decisions and decisions and decisions and decisions and decisions are also decisions and decisions are also dec | vork is that it nals to make and improve | The use of techniques, especoncerns about prequiring care information. | advanced image processing cially in the medical field, raises patient privacy and data security, eful handling of sensitive |
| The positive is can help med more informed patient outcome. Analyse The | dical profession decisions a nes. is Work By Thinking | vork is that it nals to make and improve The Tools this | The use of techniques, especancerns about prequiring care information. | advanced image processing cially in the medical field, raises patient privacy and data security, aful handling of sensitive |

| Analyse This Work By | The Tools That Assessed | What is the Structure of this |
|------------------------------|---------------------------|-------------------------------|
| Critical Thinking | this Work | Paper |
| The proposed advanced | TensorFlow or PyTorch for | 1) Abstract |
| multi-modality image fusion | Xception,numpy and scipy. | 2) Introduction |
| approach, integrating NSCT | | 3) Literature Review |
| and Xception, presents | | 4) Experimental Analysis |
| promising diagnostic | | 5) Conclusion |
| enhancements, but critical | | 6) References |
| considerations include | | |
| computational complexity, | | |
| interpretability challenges, | | |
| and the need for transparent | | |



---End of Paper 11---

| 12 | | | | | |
|-----------------------|---------------|-------------------------------------------------------------|--------------------------|--|--|
| Reference in APA | | L. Wang, J. Zhang, Y. Liu, J. Mi and J. Zhang, "Multimodal | | | |
| format | | 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 Me | <u>edical</u> | Lifang wang, Jin Zhang, Yang Liu, Jia | Medical image fusion, G- | | |
| Image Fusion Base | ed on | Mi, Jiong Zhang | CNNs, Gabor | | |
| Gabor Representation | | | representation, | | |
| Combination of Multi- | | convolutional neural | | | |
| CNN and Fuzzy N | <u>leural</u> | | network, fuzzy neural | | |
| Network] | <u>IEEE</u> | | network. | | |

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

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

| | 2 | Fuzzy neural network | The fuzzy neural network | A Fuzzy neural network |
|---|---|-------------------------------|----------------------------|----------------------------|
| | | effectively fuses the outputs | effectively fuses the | may require more training |
| | | of G-CNNs, improving | outputs of G-CNNs, | data and longer training |
| | | image fusion quality. | leading to improve image | time. |
| | | | fusion quality. | |
| _ | 3 | The proposed fusion method | Objective evaluation | The performance |
| | 5 | The proposed fusion method | Objective evaluation | The performance |
| | | is compared with nine recent | provides quantitative | comparison may depend |
| | | state-of-the-art multimodal | measures of performance. | on the datasets used for |
| | | fusion methods using | Comparative analysis helps | evaluation. Sensitivity to |
| | | mutual information, spatial | assess the proposed method | metric choice: Different |
| | | frequency, standard | against existing | metrics may provide |
| | | deviation, and edge | approaches. | varying perspectives on |
| | | retention information. | | the method's |
| | | | | performance. |
| | | | | |

<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).</p>

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

| retention | | overall fused image |
|--------------|--|---------------------|
| information. | | quality. |

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 | Contribution & The |
|---------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------|
| | | Solution | Value of this Work |
| Input CT and MR images of brain. | Output 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 | |
| Positive Impact | of this Solution in Th | information. | Negative Impact of this |
| 1 ostive impact (| or this solution in Th | ns i roject Domain | Solution in This |
| | | | Project Domain |
| The method outperforms other fusion methods in objective | | | |
| evaluation and visual quality, with significant improvements, | | | |
| spatial frequency, information. | spatial frequency, standard deviation and edge retention information. | | |

| Analyse This Work by Critical | The Tools That | What is the | | |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--|--|
| Thinking | Assessed this Work | 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. | 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 | | |
| Diagra | am/Flowchart | V. Conclusion | | |
| G-CNNs Construction Gabor filter 1 Gabor filter 2 Gabor filter 36 Gabo | | | | |
| Computing Gabor Representation pairs of CT and MR MR FIGURE 2. Multimodal medical image fusion process based on | G-CNNs G-CNNs G-CNNs G-CNNs Input Hidd G-CNNs and fuzzy neural network. | CT/MR | | |

---End of Paper 12---

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

| 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 | Moderating | Mediating |
|---------------------------|-------------|------------|---------------|
| | Variable | variable | (Intervening) |
| | | | variable |
| | | | |
| | | | |

Relationship Among The Above 4 Variables in This article

| | of this Work |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------|
| | |
| An image The reconstructe d fused image 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. | erforms state-of-the-art |

Positive 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.

Negative Impact of this Solution in This Project Domain

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

---End of Paper 13---

| - | |
|---|---|
| п | 1 |
| | 4 |
| | - |

| Reference in APA | X. Fu, L. Bi, A. Kumar, M. Fulham and J. Kim, "Multimodal | | |
|---------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--|
| format | Spatial Attention Module for Targeting Multimodal PET-CT Lung | | |
| | Tumor Segmentation," in IEEE Journal of Biomedical and Health | | |
| | Informatics, vol. 25, no. 9 | 9, pp. 3507-3516, Sept. 2021, Doi: | |
| | 10.1109/JBHI.2021.3059453 | 3. | |
| URL of the Reference | Authors Names and | Keywords in this Reference | |
| | Emails | | |
| Multimodal Spatial | Xiaohang Fu, Lei Bi, | Convolutional Neural Network | |
| Attention Module for | Ashnil Kumar, Michael | (CNN), Multimodal Image | |
| Targeting Multimodal | Fulham and Jinman Kim | Segmentation, Positron Emission | |
| PET-CT Lung Tumor | T umum und Jimman IXIII | Tomography-Computed | |
| Segmentation IEEE | | Tomography (PET-CT) | |
| Journals & Magazine | | Tomography (LT-CT) | |
| | | | |
| IEEE Xplore | | | |
| | | | |
| The Name of the | The Goal (Objective) of | What are the components of it? | |
| The Name of the Current Solution | The Goal (Objective) of this Solution & What is | What are the components of it? | |
| | | What are the components of it? | |
| Current Solution | this Solution & What is | What are the components of it? | |
| Current Solution (Technique/ Method/ | this Solution & What is the problem that need to | What are the components of it? | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ | this Solution & What is the problem that need to | What are the components of it? | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ | this Solution & What is the problem that need to | What are the components of it? The proposed deep learning | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc) | this Solution & What is the problem that need to be solved | | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc) Multimodal Spatial | this Solution & What is the problem that need to be solved Goal: To improve the | The proposed deep learning | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc) Multimodal Spatial Attention Module for | this Solution & What is the problem that need to be solved Goal: To improve the accuracy of tumor | The proposed deep learning framework uses a multimodal spatial | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc) Multimodal Spatial Attention Module for Targeting Multimodal | this Solution & What is the problem that need to be solved Goal: To improve the accuracy of tumor segmentation in PET-CT | The proposed deep learning framework uses a multimodal spatial attention module and a convolutional | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc) Multimodal Spatial Attention Module for Targeting Multimodal PET-CT Lung Tumor | this Solution & What is the problem that need to be solved Goal: To improve the accuracy of tumor segmentation in PET-CT images using a deep- | The proposed deep learning framework uses a multimodal spatial attention module and a convolutional neural network backbone to segment | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc) Multimodal Spatial Attention Module for Targeting Multimodal PET-CT Lung Tumor | this Solution & What is the problem that need to be solved Goal: To improve the accuracy of tumor segmentation in PET-CT images using a deep- learning based framework | 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- | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc) Multimodal Spatial Attention Module for Targeting Multimodal PET-CT Lung Tumor | this Solution & What is the problem that need to be solved Goal: To improve the accuracy of tumor segmentation in PET-CT images using a deep- learning based framework with a multimodal special | 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- | |
| Current Solution (Technique/ Method/ Scheme/ Algorithm/ Model/ Tool/ Framework/etc) Multimodal Spatial Attention Module for Targeting Multimodal PET-CT Lung Tumor | this Solution & What is the problem that need to be solved Goal: To improve the accuracy of tumor segmentation in PET-CT images using a deep- learning based framework with a multimodal 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- | |

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

Major Impact Factors in this Work

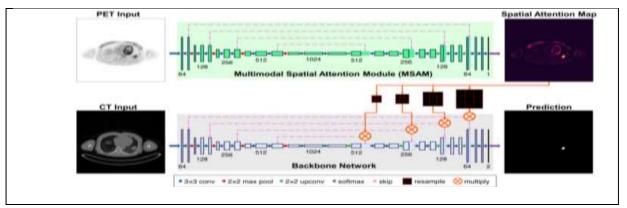
| Dependent Variable | Independent | Moderating | Mediating |
|-----------------------|----------------------|------------------------|-----------------------|
| | Variable | variable | (Intervening) |
| | | | variable |
| Effectiveness of | Multimodal spatial | Type of cancer: The | Spatial attention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

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 | This work presents a |
| A multimodal PET-CT image, which consists of PET and CT image. | A segmentatio n map that identifies tumor regions in the image. | PET and CT modalities for improved tumor segmentation accuracy. It can handle varied anatomical and functional features. The framework outperforms stateof-the-art methods in segmentation accuracy. | |
| | | | |

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

Diagram/Flowchart



---End of Paper 14---

| | _ |
|---|--------|
| | - |
| _ | \sim |

| Reference in APA format | K. Kusram, S. Transue and | d MH. Choi, "Two-Phase |
|------------------------------|---------------------------------|-------------------------------|
| | Multimodal Image Fusion | Using Convolutional Neural |
| | Networks," 2021 IEEE Inter | national Conference on Image |
| | Processing (ICIP), Anchorage, | AK, USA, 2021, pp. 1874-1878, |
| | doi: 10.1109/ICIP42928.2021.9 | 9506703. |
| IIDI -£ 4l | A41 N 1 E 2 | V |
| URL of the | Authors Names and Emails | Keywords in this Reference |
| Reference | | |
| https://ieeexplore.ieee.org/ | Ch. Hima Bindu, K. Veera | Coarse Fusion Network (CFN), |
| document/9506703 | Swamy | Refining Fusion Network |
| | | (RFN), Depth and Thermal |
| | | Synchronized Streams, Image- |
| | | space Transformations |
| The Name of the Current | The Goal (Objective) of this | What are the components of |
| | Solution & What is the | it? |
| Solution (Technique/ | | 10.5 |
| Method/ Scheme/ | problem that needs to be | |
| Algorithm/ Model/ Tool/ | solved | |
| Framework/ etc) | | |
| Two-phase multimodal | Goal: To present a novel | The components of the |
| image fusion using | method for fusing multiple | proposed solution include a |
| convolutional neural | imaging modalities at a per- | hypergraph-based manifold |
| networks | pixel level. By employing a | regularization, a multi-modal |

two-phase non-linear registration method.

The Problem: fusion multiple imaging modalities at a per-pixel level, challenging due to the variations in sensor and lens intrinsics. Traditional calibration methods have achieving limitations in accurate alignment.

feature selection method, and a multi-linear multi-task regression model for predicting cognitive scores. The solution also involves integrating SNP, methylation, DNA and functional magnetic resonance imaging (fMRI) data improve classification biomarker accuracy and 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 | It reduces the computational complexity of the registration process. | it may not be able to handle non-linear deformations. |
| | images. | | |
| 2 | This is the second stage of | it can handle non-linear | increased computational |
| | the proposed method, where per-pixel displacements are predicted to refine the alignment obtained in the first stage. | deformations | 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. | | |
| | Maior Im | pact Factors in this Work | |

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

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 |
|---------------|-----------------|
| The input of | The output is |
| the paper is | a fused image |
| the | that combines |
| development | multiple |
| of a two- | imaging |
| phase | modalities at |
| multimodal | a per-pixel |
| image fusion | level, |
| method using | resulting in an |
| convolutional | efficient and |
| neural | accurate |
| networks. | image |
| | registration. |

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. 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 medical imaging and autonomous driving.

Positive Impact of this Solution in This Project Domain

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.

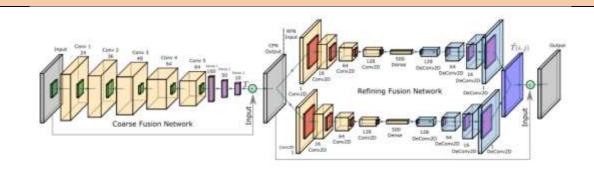
Negative Impact of this Solution in This Project Domain

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.

| Analyse This Work By | The Tools That Assessed this | What | is | the |
|----------------------|------------------------------|--------------|--------|-------|
| Critical Thinking | Work | Structure of | this I | Paper |

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

Diagram/Flowchart



---End of Paper 15---

| | ce in APA mat | Barrett, J., & Viana, T. (2022). EMM-LC Fusion: Enhanced Multimodal Fusion for Lung Cancer Classification. <i>AI</i> , <i>3</i> (3), | |
|----------------------------|-------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| URL of the | e Reference | Authors Names and Keywords in this Reference Emails | |
| https://www 673-2688/3/ | v.mdpi.com/2 /3/38 | James Barrett and Thiago Viana | Lung cancer, Diagnosis, Machine learning, classification, multimodal, fusion. |
| Current (Techniqu | me of the Solution ne/ Method/ 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 | Enhanced lung | cancer | Pre-processing, feature extraction |
| Fusion for Lung Cancer | classification | using | from pre trained Aligned eXception |
| Classification. | multimodal fusion. | | 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. |

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

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

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).</p>

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

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 7 | This Solution | Contribution & The Value |
|-----------------------------------------------------|-----------------------------------------------------------------------|-----------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------|
| | | | | of This Work |
| Input Set of pre- processed CT scans of the lung. | Output Classificatio n of the CT scan as either malignant or benign. | fusion ap combines in multiple mode CT scans and | a multimodal oproach that formation from alities, including clinical data, to accuracy of lung on. | |
| Positive Impact of this Solut Project Domain | | | | pact of this Solution in This Project Domain |
| It's potential to improve the lung cancer det | accuracy of | | It is important to carefully consider the potential benefits and limitations of the approach in the context of specific healthcare settings are patient populations. | |
| Analyse This Work by Critical Thinking | | | That Assessed Work | What is the Structure of this Paper |

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

---End of Paper 16--

| 17 | |
|-------------------------|------------------------------------------------------------|
| Reference in APA format | Y. Zhang, H. Zhang, L. Xiao, Y. Bai, V. D. Calhoun and YP. |
| | 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 | Authors Names and Emails Keywords in this Reference |
| Reference | Rey words in this reference |

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

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

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

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 | The contributions of this |
| The input | The output is | algorithm called HMF that | work include combining |
| used in this | the validate | combines information from | complementary |
| research | their | diverse sources for improved | information from multi- |
| paper | approach on | accuracy in diagnosing complex | |
| | | brain disorders. The method | hypergraph-based |

includes both synthetic data and real imaging and genetics samples from datasets. The schizophrenia paper introduces a study and novel show that algorithm **HMF** called HMF outperforms that combines several information competing from these methods. diverse sources for improved accuracy in diagnosing complex brain disorders.

uses hypergraph-based manifold regularization capture high-order relationships among subjects and enforce regularization based on both interand intra-modality relationships.

similarity matrix to better characterize highorder structural relationships, employing novel manifold regularization incorporate term to structural information both within and across modalities, and incorporating both sparsity and manifold regularization circumvent the overfitting problem. The value of this work lies in its potential to improve the accuracy of complex diagnosing 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 | Negative Impact of this Solution in This | | |
|----------------------------------------------|------------------------------------------------|--|--|
| Project Domain | Project Domain | | |
| The positive impact of this solution in this | one potential limitation is that the algorithm | | |
| project domain is that it provides a more | is still based on linear regression and may | | |
| accurate and comprehensive approach to | 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.

| with these disorders. | | | | | |
|----------------------------------|----------------|------------|----------|------------|---------------|
| Analyse This Work By | The Tools Th | nat Assess | sed this | What is | the Structure |
| Critical Thinking | V | Vork | | of this Pa | aper |
| the authors used various | false discove | ery rate | (FDR), | I. | Introduction |
| statistical and machine learning | MTL, SNF | -SVM, | MMN, | II. | Methods |
| tools to develop and validate | gCAM-CCL, I | MRMF, ar | nd GSSL | III. | Results |
| their algorithm, including | | | | IV. | Discussion |
| hypergraph-based manifold | | | | V. | Conclusion |
| 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. | | | | | |
| | Diagram/Fl | owchart | | | |
| | | | <u> </u> | | |
| | | | | | |

---End of Paper 17--

| 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 | Keywords in this Reference | |
| ORL of the Reference | Emails | Key words in this Reference | |
| https://iopscience.iop.or | Kaushik Pratim Das and | PET&CT imaging, Medical image | |
| g/article/10.1149/10701. | Chandra J | fusion, Lung cancer diagnosis, | |
| 3649ecst/pdf | | Multimodalarity imaging | |
| The Name of the | The Goal (Objective) of | What are the components of it? | |
| Current Solution | this Solution & What is | | |
| (Technique/ Method/ | the problem that need to | | |
| Scheme/ Algorithm/ | be solved | | |
| Model/ Tool/ | | | |
| Framework/ etc) | | | |
| Multimodal | The goal of medical image | multiple medical images, image | |
| Classification on | fusion is to combine | registration techniques, image fusion | |
| PET/CT Image Fusion | multiple medical images to | algorithms, and image quality | |
| for Lung Cancer | produce a single image that | assessment methods. | |
| | 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. | | |

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

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

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 7 | This Solution | Contribution in This Work |
|---------------------------------------|-------------|----------------|-----------------|-------------------------------|
| Input Output | | Comprehensi | ve coverage of | The authors' work provides a |
| Multiple | Classified | medical i | mage fusion | valuable resource for |
| PET and CT | Lung cancer | techniques for | or lung cancer | researchers, medical |
| images | multimodal | diagnosis, in | ncluding recent | professionals, and anyone |
| | images | advances and | d the impact of | interested in medical image |
| | | deep learning | techniques. | fusion for lung cancer |
| | | | | diagnosis. |
| Positive Impact of this Solution in T | | ition in This | Negative Im | pact of this Solution in This |
| Project Domain | |] | 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 | The Tools T | That Assessed | What is the Structure of this |
|------------------------------|----------------------------------------------|----------------------------------------------------------|----------------------------------------------------------|
| Critical Thinking | | Work | Paper |
| The provided information is | TensorFlow | or PyTorch, | 1) Abstract |
| very useful and the detailed | openCv | | 2) Introduction |
| explanation of process helps | | | 3) Literature Review |
| to build efficient model. | | | 4) Discussions |
| | | | 5) Conclusion |
| | Diagran | n/Flowchart | |
| | (a) Pixel based fined images | Feature | ompetation and Clinical aftermation Evaluation |
| PET and CT Images | (h)Multi- source extracted features | Feature level | nempotation and Clinical aformation Evaluation |
| | (c)Frature Extraction | Multi- decisions based on extracted features | Decision- based fusion |
| | | | Computation ind Clinical Information Evaluation |

--End of Paper 18—

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

| https://www.hindawi.c om/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 | The Goal (Objective) of | What are the components of it? |
| Current Solution | this Solution & What is the | |
| (Technique/ Method/ | problem that need to be | |
| Scheme/ Algorithm/ | solved | |
| Model/ Tool/ | | |
| Framework/ etc) | | |
| Social Engineering | Aim is to detect and | Preprocessing using bilateral |
| Bottu Engineering | Ann is to detect and | Preprocessing using bilateral |
| Optimization with | categorize the presence of | filtering, image segmentation using |
| | | |
| Optimization with | categorize the presence of breast cancer using | filtering, image segmentation using |
| Optimization with Deep Transfer | categorize the presence of breast cancer using | filtering, image segmentation using LEDNet model, feature extraction |
| Optimization with Deep Transfer Learning-Based Breast | categorize the presence of breast cancer using | filtering, image segmentation using LEDNet model, feature extraction using ResNet-18 model, image |
| Optimization with Deep Transfer Learning-Based Breast Cancer Detection and | categorize the presence of breast cancer using | filtering, image segmentation using LEDNet model, feature extraction using ResNet-18 model, image classification using RNN and |
| Optimization with Deep Transfer Learning-Based Breast Cancer Detection and Classification Model | categorize the presence of breast cancer using | filtering, image segmentation using LEDNet model, feature extraction using ResNet-18 model, image classification using RNN and hyperparameter tuning using SEO |

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 | It preserves the edges while | It may not be effective in |
| | bilateral filtering which | smoothing the image. | removing all types of |
| | smoothens the images | | noise. |
| | without changing the edges. | | |

| 2 | Ground truth which | It provides a reference for | It requires manual | |
|-----------------------------------|--------------------------------|------------------------------|-----------------------------|--|
| | involves labeling the images | the classification model. | labeling, which can be | |
| | as benign, malignant, or | | time-consuming and | |
| normal. | | | prone to errors. | |
| | | | | |
| 3 | Image segmentation using | It reduces the complexity | It may not be effective in | |
| | LEDNet model segments | of the image and focuses on | segmenting all types of | |
| | the breast region from the | the region of interest. | breast tissue. | |
| | ultrasound image. | | | |
| 4 | Feature extraction process | It can capture complex | It may require a large | |
| | using CNN-based ResNet- | patterns and features that | amount of data and | |
| | 18 model from the | are difficult to detect | computational resources. | |
| | segmented image using a | manually. | | |
| | deep learning model. | · | | |
| | 1 0 | T. 11 .1 .1 .1 | | |
| 5 | Training images (BUSI | It allows the model to learn | The dataset may not be | |
| | dataset) which involves | from a large amount of | representative of all types | |
| | training the classification | data. | of breast tissue. | |
| | model using a dataset of | | | |
| | ultrasound images. | | | |
| 6 | Image classification using | It can accurately classify | It may require a large | |
| | recurrent neural network | the presence of breast | amount of data and | |
| | that classifies the ultrasound | cancer. | computational resources. | |
| | image as benign, malignant, | | | |
| | or normal | | | |
| 7 | Hyperparameter tuning | It can improve the | It may require a large | |
| | using SEO algorithm that | performance of the model. | number of computational | |
| | optimizes the | | resources. | |
| | hyperparameters of the | | | |
| | classification model using a | | | |
| | social engineering | | | |
| | optimization algorithm. | | | |
| | | | | |
| Major Impact Factors in this Work | | | | |

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

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 |

| Input | Output |
|------------|--------------|
| Photoacous | Classificati |
| tic | on of the |
| multimodal | input image |
| images of | as benign, |
| breast | malignant, |
| tissue | or normal |
| | |

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.

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.

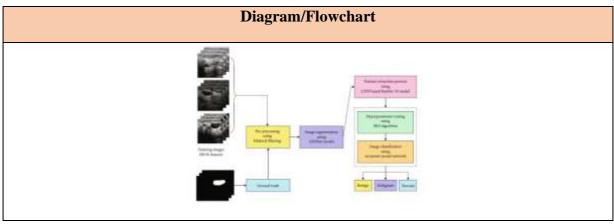
Positive Impact of this Solution in This Project Domain

It's potential to significantly improve breast cancer diagnosis and treatment, ultimately leading to better patient outcomes.

Negative Impact of this Solution in This Project Domain

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



--End of Paper 19--

| 20 | | | |
|-----------------------------|-------------------------------------------------------------|-----------------------------------------------|--|
| Reference in APA | Haribabu, M., & Guruviah, V. (2023). An Improved Multimodal | | |
| format | Medical Image Fusion App | broach Using Intuitionistic Fuzzy Set | |
| | and Intuitionistic Fuzzy Cro | oss-Correlation. <i>Diagnostics</i> , 13(14), | |
| | 2330. https://doi.org/10.3390/diagnostics13142330 | | |
| | 2330. https://doi.org/10.3330/dragnostics13142330 | | |
| URL of the Reference | Authors Names and | Keywords in this Reference | |
| | Emails | | |
| https://www.mdpi.com/ | Maruturi Haribabu and | Medical imaging, image fusion, | |
| 2075-4418/13/14/2330 | Velmathi Guruvaiah | disease diagnosis, intuitionistic | |
| | | fuzzy set, intuitionistic fuzzy image, | |
| | | subjective and objective analysis. | |
| | | subjective and objective analysis. | |
| The Name of the | The Goal (Objective) of | What are the components of it? | |
| Current Solution | this Solution & What is | | |
| (Technique/ Method/ | the problem that need to | | |
| Scheme/ Algorithm/ | be solved | | |
| Model/ Tool/ | | | |
| Framework/ etc) | | | |
| ŕ | | | |
| An Improved | Goal or objective: To | The proposed solution uses | |
| Multimodal Medical | propose an improved | Intuitionistic Fuzzy Set and | |
| Image Fusion Approach | approach to multimodal | Intuitionistic Fuzzy Cross- | |
| using Intuitionistic | medical image fusion using | Correlation. | |

| Fuzzy Set and | intuitionistic fuzzy set and | |
|----------------------|------------------------------|--|
| Intuitionistic Fuzzy | intuitionistic fuzzy cross- | |
| Cross-Correlation | correlation. | |
| | Problem: The need for | |
| | better quality medical | |
| | images that can aid in the | |
| | diagnostic process. | |
| | | |

| | Process Steps | Advantage | Disadvantage |
|---|------------------------------|-------------------------------|----------------------------|
| | | | (Limitation) |
| 1 | Fuzzification of registered | It helps to handle the | may lead to a loss of |
| | input images | uncertainty and | information. |
| | | imprecision in the input | |
| | | images. | |
| 2 | Creation of intuitionistic | It helps to enhance the | may lead to a loss of |
| | fuzzy images | intensity levels of the input | spatial information. |
| | | images | |
| 3 | Fusing the intuitionistic | It helps to obtain a single | may lead to a loss of some |
| | fuzzy images | fused image with more | information during the |
| | | complementary | fusion process. |
| | | information and better | |
| | | quality. | |
| 4 | Defuzzification of the final | It helps to obtain a crisp | may lead to a loss of some |
| | enhanced fused image | image that can be easily | information during the |
| | | interpreted by medical | defuzzification process |
| | | professionals. | |
| | Major I | mnact Factors in this Work | |

Major Impact Factors in this Work

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

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

| Positive 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 inherent uncertainty imprecision in medical imprecision in The Solution in The Solution has challenges which increased computational complexity difficulty in interpretation. | | | | | |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------|-----------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--|--|
| Analyse This Work By Critical Thinking | | That Assessed 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 to MATLAB, SPSS. | ools include ImageJ, and | Abstract Introduction Related Works Materials and Methods Proposed Fusion Method Experimental Results and Conclusions References | | |
| | Diagrai | m/Flowchart | | | |
| MRI Image → Fuzzification → Fuzzification → CT Image | Calculate intuition fuzzy image Calculate intuition fuzzy image | → Decomposition | of each image block | | |

--End of Paper 20—

2.2 COMPARISION TABLE:

| Author | Year | Approach | Description |
|--------------------|------|------------------------|--------------------------------------|
| Zsoter N, Bandi P, | 2012 | Lung affinity map | An automated method for |
| Szabo G, Toth Z, | | generation, nodule | detecting lung nodules in PET-CT |
| Bundschuh R. A., | | detection, nodule | studies, significantly reducing |
| Dinges J, Papp L. | | classification. | localization time and proving |
| | | | effective in clinical evaluation for |
| | | | oncology practices. |
| Ch. Hima Bindu | 2014 | Automatic | Feature-level image fusion method |
| and Dr. K. Veera | | Segmentation Process, | using content-based automatic |
| Swamy | | Feature-Level Fusion | segmentation, enhancing |
| | | and Performance | multimodal image information |
| | | Evaluation Metrics | into a meaningful and informative |
| | | | fused image. |
| Himanshi, V. | 2014 | Gray scale conversion, | Decomposing the source images |
| Bhateja, A. | | PCA, DTCWT | using DTCWT and applying PCA |
| Krishn and A. | | decomposition, and | in the complex wavelet domain to |
| Sahu | | image fusion | fuse the images. |
| Z. Guo, X. Li, H. | 2018 | Deep Convolutional | CNN-based segmentation system |
| Huang, N. Guo | | Neural Network | for soft tissue sarcoma detection |
| and Q. Li | | (CNN), Multi-Modality | from multi-modal medical images, |
| | | image processing and | investigating diverse fusion |
| | | Fusion Techniques. | schemes for improved accuracy in |
| | | | biomedical imaging analysis. |
| M B | 2018 | DWT and Inverse DWT | Preprocessing of images, |
| Abdulkareem | | | decomposition using DWT, |
| | | | obtaining the fused image via |
| | | | Inverse DWT and postprocessing |
| | | | the image |
| K. Vanitha, D. | 2019 | Hybrid 11-10 | A hybrid L1-L0 decomposition- |
| Satyanarayana | | decomposition model, | based two-scale fusion method for |
| and M. N. G. | | Weighted average | multimodal medical images, |
| Prasad | | fusion rule, Average | aiming to enhance information |

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

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

| | | using various | via machine learning for improved |
|-------------------|------|--------------------------|--------------------------------------|
| | | evaluation metrics such | lung cancer detection. |
| | | as sensitivity, | |
| | | specificity, accuracy, | |
| | | and F1 score. | |
| Y. Zhang, H. | 2022 | Hypergraph | Hypergraph-based Multi-modal |
| Zhang, L. Xiao, | | Representation, Inter- | data Fusion (HMF) algorithm for |
| Y. Bai, V. D. | | and Intra-Modality | integrating imaging and genetics |
| Calhoun and Y | | Relationships and HMF | data, enhancing schizophrenia |
| P. Wang | | Algorithm | classification accuracy by |
| | | | capturing complex interactions |
| | | | among risk genes, environmental |
| | | | factors, and abnormal brain |
| | | | regions. |
| Kaushik Pratim | 2022 | Multiple medical | Efficient medical image fusion |
| Das and Chandra J | | images, image | techniques, explores recent |
| | | registration techniques, | advancements, and assesses the |
| | | image fusion | impact of deep learning in |
| | | algorithms, and image | automating the process for |
| | | quality assessment | enhanced image quality and |
| | | methods | clinical information retention. |
| Maha M. | 2022 | Preprocessing: bilateral | A highly advanced and accurate |
| Althobaiti, Amal | | filtering, LEDNet | solution for breast cancer detection |
| Adnan Ashour, | | model for image | and classification, which has the |
| Nada A. Alhindi, | | segmentation,x Feature | potential to significantly improve |
| Asim Althobaiti, | | extraction: ResNet-18 | the diagnosis and treatment of |
| Romany F. | | model, Image | breast cancer. |
| Mansour, Deepak | | classification: RNN and | |
| Gupta and Ashish | | hyperparameter tuning | |
| Khanna | | with SEO algorithm | |
| Haribabu, M., and | 2023 | Intuitionistic Fuzzy Set | An intuitionistic fuzzy set |
| Guruviah, V | | and Intuitionistic Fuzzy | and intuitistic fuzzy cross- |
| | | Cross-Correlation | 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 | System' | System' | Features | Performa | Advant | Limitat | Results |
|------|---------|----------|----------|-----------|-----------|----------|----------|--------------|
| | Goal | S | S | /Charac | nce | ages | ions | |
| | | Compo | Mecha | teristics | | | /Disadv | |
| | | nents | nism | | | | antages | |
| LIFA | The | Author | The | The | The | Integrat | The | The |
| NG | goal of | used | system | proposed | proposed | es the | propose | proposed |
| WAN | the | Gabor | uses | solution | solution | rich | d | solution |
| G, | propos | represe | Gabor | outperfor | achieved | texture | solution | outperform |
| JIN | ed | ntation, | represe | ms nine | better | features | has the | s methods |
| ZHA | solutio | multi- | ntation, | recent | performa | and | disadva | by |
| NG, | n is to | CNNs | multi- | states of | nce than | clear | ntage of | significantl |
| YAN | impro | and | CNN, | the art | other | edge | increase | у |
| G | ve the | fuzzy | and | multimo | comparati | informa | d | enhancing |
| LIU, | quality | neural | fuzzy | dal | ve fusion | tion of | comput | objective |
| JIA | of | network | neural | fusion | methods | differen | ational | evaluation |
| MI, | multi | s for | network | methods | in | t images | comple | and visual |
| AND | modal | obtainin | techniq | in terms | objective | into a | xity and | quality |
| JION | medica | g fused | ues to | of | evaluatio | single | longer | measures, |
| G | 1 | images. | enhance | average | n and | fused | training | achieving |
| ZHA | image | | the | mutual | visual | image, | time. | up to 13% |
| NG | fusion. | | texture | informati | quality. | which | | improveme |
| 2021 | | | features | on, | | improve | | nt in |
| | | | and | spatial | | s the | | mutual |
| | | | edge | frequenc | | quality | | informatio |

| | | | informa | y, | | of | | n, 20% in |
|-------|---------|----------|----------|-----------|-------------|----------|----------|-------------|
| | | | tion of | standard | | image | | spatial |
| | | | the | deviation | | fusion | | frequency, |
| | | | source | , and | | and | | 14.4% in |
| | | | images | edge | | assists | | standard |
| | | | and | retention | | doctors | | deviation, |
| | | | generat | informati | | in | | and 43% in |
| | | | e a | on. | | disease | | edge |
| | | | high- | | | diagnos | | retention. |
| | | | quality | | | is. | | |
| | | | fused | | | | | |
| | | | image. | | | | | |
| Ch. | The | image | Propose | the use | The | it | it may | The output |
| Hima | goal of | fusion | d | of multi- | proposed | provide | not be | is a |
| Bindu | this | using a | method | modal | image | s a | suitable | generalized |
| , K. | solutio | propose | focuses | image | fusion | unified | for all | framework |
| Veera | n is to | d | on | fusion, a | method | framew | scenario | of image |
| Swam | achiev | region- | region- | novel | utilizes | ork for | s, and | fusion for |
| у | e less | based | based | conceptu | region- | multi- | some | supervised |
| | compl | fusion | fusion, | al image | based | modal | modific | learning in |
| | ex | method | merging | fusion | feature | image | ations | biomedical |
| | fusion | with | selected | architect | level | processi | may be | image |
| | and | evaluati | regions | ure, the | fusion, | ng, | necessa | |
| | impro | on | to | use of | overcomi | which | ry. | |
| | ve the | based | reconstr | Convolut | ng the | can | | |
| | perfor | on | uct the | ional | drawback | guide | | |
| | mance | Fusion | final | Neural | s of pixel- | the | | |
| | of | Symmet | fused | Network | level | method | | |
| | image | ry and | image. | S | methods. | ology | | |
| | fusion | Peak | Evaluati | (CNNs), | It | design | | |
| | metho | Signal | on of | and the | achieves | for | | |
| | ds | | the | evaluatio | better | various | | |
| | compa | | method | n of | performa | | | |

| existin Ratio. metrics nce existing ions. | |
|-------------------------------------------|--|
| | |
| g like differenc methods, | |
| metho fusion es across as | |
| ds. symmet different evidenced | |
| ry and fusion by higher | |
| peak schemes. Fusion | |
| signal- These Symmetr | |
| to-noise features y and | |
| ratio contribut Peak | |
| (PSNR) e to Signal to | |
| for improve Noise | |
| perform d Ratio | |
| ance accuracy (PSNR) | |
| assessm and values. | |
| ent. robustne The | |
| ss of method is | |
| medical visually | |
| image and | |
| segment quantitati | |
| ation. vely | |
| evaluated | |
| with CT- | |
| MRI and | |
| MRI-PET | |
| images, | |
| demonstr | |
| ating its | |
| effectiven | |
| ess in | |
| medical | |
| diagnostic | |
| S. | |

| Hima | То | Gray | Decom | Shift | Reported | Improv | Comput | A fused |
|--------|---------|----------|----------|------------|-------------|----------|-----------|-------------|
| nshi, | presen | scale | posing | invarianc | to be | ed | ational | image with |
| Vikra | t an | convers | the | e, high | satisfactor | visual | intensit | higher |
| nt | impro | ion, | source | direction | y, with | quality | y of | fusion |
| Bhatej | ved | DTCW | images | ality, and | higher | of fused | DTCW | metric |
| a, | fusion | T | using | feature | values of | images | T, | values |
| Abhin | approa | decomp | DTCW | enhance | fusion | | potentia | |
| av | ch for | osition, | T and | ment | metrics | | lly | |
| Krish | medica | PCA | applyin | propertie | supportin | | increasi | |
| n and | 1 | and | g PCA | S | g the | | ng | |
| Akan | images | image | in the | | improvem | | processi | |
| ksha | using | fusion | comple | | ent in | | ng time | |
| Sahu | PCA | | X | | visual | | and | |
| | and | | wavelet | | quality of | | cost, | |
| | DTC | | domain | | the fused | | and the | |
| | WT. | | to fuse | | image. | | risk of | |
| | | | the | | | | informa | |
| | | | images. | | | | tion loss | |
| | | | | | | | during | |
| | | | | | | | fusion | |
| Z. | a | a multi- | Concept | multi- | The paper | it | it may | The output |
| Guo, | genera | modal | ual | modal | proposes | provide | not be | is a |
| X. Li, | lized | convolu | design | image | a | s a | suitable | generalized |
| H. | frame | tional | for | fusion, a | generalize | unified | for all | framework |
| Huan | work | neural | image | novel | d | framew | scenario | of image |
| g, N. | of | network | fusion | conceptu | framewor | ork for | s, and | fusion for |
| Guo | image | approac | scheme | al image | k for | multi- | some | supervised |
| and | fusion | h for | s, | fusion | image | modal | modific | learning in |
| Q. Li | for | medical | includin | architect | fusion in | image | ations | biomedical |
| | superv | image | g fusing | ure, the | biomedic | processi | may be | image. |
| | ised | segment | at | use of | al image | ng, | necessa | |
| | learnin | ation, | feature | Convolut | analysis | which | ry. | |
| | g to | which | level, | ional | using | can | | |

| | imple | includes | fusing | Neural | deep | guide | | |
|-------|---------|-----------|-----------|-----------|-------------|----------|-----------|------------|
| | ment | three | at | Network | convoluti | the | | |
| | the | scheme | classifie | s | onal | method | | |
| | fusion | s for | r level, | (CNNs), | neural | ology | | |
| | schem | fusing | and | and the | networks. | design | | |
| | es | informa | fusing | evaluatio | The | for | | |
| | based | tion | at | n of | fusion | various | | |
| | on | from | decision | performa | networks | applicat | | |
| | deep | differen | level. | nce | outperfor | ions. | | |
| | CNN | t image | | differenc | m single- | | | |
| | to | modaliti | | es across | modality | | | |
| | impro | es: | | different | counterpa | | | |
| | ve the | fusing | | fusion | rts on the | | | |
| | accura | at | | schemes. | TCIA | | | |
| | cy and | feature | | These | Soft- | | | |
| | robust | level, | | features | tissue- | | | |
| | ness of | fusing | | contribut | Sarcoma | | | |
| | medica | at | | e to | dataset, | | | |
| | 1 | classifie | | improve | demonstr | | | |
| | image | r level, | | d | ating their | | | |
| | segme | and | | accuracy | potential | | | |
| | ntation | fusing | | and | for multi- | | | |
| | using | at | | robustne | modal | | | |
| | multi- | decision | | ss of | medical | | | |
| | modal | level. | | medical | image | | | |
| | CNN. | | | image | analysis. | | | |
| | | | | segment | | | | |
| | | | | ation. | | | | |
| Moha | То | DWT | Preproc | Preservat | Achieves | Preserv | May | A fused |
| mmed | enhanc | and | essing | ion of | around | ation of | introduc | image with |
| Basil | e the | Inverse | of | both the | 90-95% | both the | e some | accurate |
| Abdul | quality | DWT | images, | spectral | more | spectral | artifacts | outcomes |
| | of | | decomp | and | accurate | and | and | preserving |

| karee | medica | | osition | anatomic | outcomes | anatomi | distortio | both |
|--------|---------|----------|----------|------------|-----------|----------|-----------|-------------|
| m | 1 | | using | al data, | and | cal data | ns in the | spectral |
| | images | | DWT, | and the | preserves | and | process | and |
| | for | | obtainin | ability to | both the | provide | ed | anatomical |
| | clinica | | g the | dilute the | spectral | s a | images. | data |
| | 1 | | fused | color | and | multi- | | |
| | diagno | | image | change. | anatomica | resoluti | | |
| | sis | | via | | 1 data | on | | |
| | throug | | Inverse | | | represe | | |
| | h | | DWT | | | ntation | | |
| | image | | and | | | | | |
| | fusion | | post- | | | | | |
| | techni | | processi | | | | | |
| | que | | ng the | | | | | |
| | | | image | | | | | |
| K.Van | То | Hybrid | uses a | Evaluati | outperfor | can | - | A fused |
| itha, | develo | 11-10 | 11-10 | on using | ms | provide | | image |
| Dr.D. | p a | decomp | decomp | objective | existing | a more | | which |
| Satya | new | osition | osition | criteria | methods | complet | | helps |
| naray | metho | model, | model | such as | in terms | e and | | researchers |
| ana | d for | Weight | and | mean, | of image | accurate | | compare |
| and | multi | ed | weighte | standard | quality | represe | | and |
| Dr.M. | modal | average | d | deviation | and | ntation | | benchmark |
| N.Giri | medica | fusion | average | , and | objective | of the | | different |
| Prasa | 1 | rule, | fusion | mutual | evaluatio | underlyi | | methods |
| d | image | Averag | rule to | informati | n. | ng | | for medical |
| | fusion | e fusion | combin | on, | | anatom | | image |
| | that | rule, | e | which | | y or | | fusion, |
| | can | Linear | detailed | allows | | patholo | | which can |
| | provid | combin | informa | for a | | gy, even | | lead to |
| | e a | ation | tion, | quantitat | | when | | further |
| | more | and | average | ive | | source | | improveme |
| | compl | Objecti | fusion | assessme | | images | | |

| | ete and | ve | rule for | nt of its | | have | | nts in the |
|--------|---------|----------|-----------|-----------|------------|----------|----------|-------------|
| | accurat | criteria | base | performa | | poor | | field. |
| | e | | layers, | nce. | | contrast | | |
| | represe | | and a | | | | | |
| | ntation | | linear | | | | | |
| | of the | | combin | | | | | |
| | underl | | ation for | | | | | |
| | ying | | the final | | | | | |
| | anato | | fused | | | | | |
| | my or | | image, | | | | | |
| | pathol | | evaluate | | | | | |
| | ogy | | d with | | | | | |
| | | | objectiv | | | | | |
| | | | e | | | | | |
| | | | criteria | | | | | |
| | | | for | | | | | |
| | | | perform | | | | | |
| | | | ance | | | | | |
| | | | compari | | | | | |
| | | | son. | | | | | |
| Jiaxin | То | A | Uses a | Combini | Efficient | Segmen | Practica | Binary |
| Li, | impro | densely | deep | ng MR | tumor | ting | 1 | segmentati |
| Houji | ve the | connect | learning | imaging | segmentat | lung | applicat | on mask |
| n | accura | ed fully | approac | modaliti | ion and | tumors | ion | that |
| Chen, | cy of | convolu | h to | es for | assessing | due to | might | identifies |
| Yanfe | lung | tional | accurate | anatomic | performa | the | be | the tumor |
| ng Li | tumor | network | ly | al and | nce with | comple | hindere | region in |
| and | segme | and a | segment | function | Dice | x and | d in | the images. |
| Yahui | ntation | hyper- | lung | al | Similarity | diverse | certain | |
| Peng | on | densely | tumors | informati | Coefficie | appeara | settings | |
| | multi- | connect | on | on, | nt (DSC) | nce of | | |
| | modal | ed CNN | multi- | utilizing | | tumors | | |
| | MR | model | modal | a novel | | on | | |

| | images | for | MR | network | | differen | | |
|-------|----------|----------|-----------|-----------|------------|-----------|-----------|--------------|
| | , which | multi- | images. | architect | | t | | |
| | is | modalit | | ure | | modaliti | | |
| | import | y fusion | | blending | | es. | | |
| | ant for | | | U-Net | | | | |
| | the | | | and | | | | |
| | classifi | | | densely | | | | |
| | cation | | | connecte | | | | |
| | of | | | d CNN | | | | |
| | tumors | | | character | | | | |
| | | | | istics | | | | |
| | | | | | | | | |
| | _ | | | | | | | |
| K SAI | То | The | The . | This | The | The | The | The results |
| ASIS | enhanc | compon | extracti | solution | proposed | advanta | limitati | of this |
| h | e the | ents of | on of | merges | solution | ges of | ons of | work show |
| RED | accura | the | fine | multiple | provides | this | this | that the |
| DY, | cy of | propose | details | medical | more | process | process | fusion |
| K | clinica | d | from the | images | accurate | include | include | process |
| KAL | 1 | solution | input | from | and | improve | comple | provides |
| YAN | diagno | include | images | PET, | informati | d | xity, | more |
| KUM | sis | the use | | MRI, | ve | accurac | processi | accurate |
| AR, | throug | of | DWT | and CT | medical | у, | ng time, | and |
| K. | h the | Discrete | and | into a | images | reduced | and | informativ |
| NAV | fusion | wavelet | PCA | single | for | data, | sensitivi | e images |
| EEN | of | transfor | algorith | image, | clinical | applica | ty to | for clinical |
| KUM | multi | m | ms, | providin | diagnosis, | bility to | input | diagnosis, |
| AR, | modal | (DWT), | followe | g | which can | multiple | quality. | which can |
| BHA | medica | Principa | d by the | accurate, | lead to | modaliti | | lead to |
| VAN | 1 | 1 | fusion | informati | better | es, and | | better |
| A. V, | images | Compo | of the | ve data | patient | reliabili | | patient |
| KRIS | • | nent | extracte | for | outcomes | ty | | outcomes |
| HNA | | Analysi | d details | clinical | and | | | and |

| PPA | | s (PCA) | into a | diagnosi | improved | | | improved |
|-------|----------|-----------|-----------|-----------|------------|-----------|---------|------------|
| H.K | | for | single | s using | healthcare | | | healthcare |
| 2019 | | image | image | advance | delivery. | | | delivery. |
| _017 | | fusion. | using a | d | | | | |
| | | | fusion | algorith | | | | |
| | | | rule. | ms like | | | | |
| | | | The | DWT | | | | |
| | | | fused | and | | | | |
| | | | image is | PCA. | | | | |
| | | | then | | | | | |
| | | | post- | | | | | |
| | | | process | | | | | |
| | | | ed to | | | | | |
| | | | enhance | | | | | |
| | | | its | | | | | |
| | | | quality | | | | | |
| | | | and | | | | | |
| | | | remove | | | | | |
| | | | any | | | | | |
| | | | artifacts | | | | | |
| Huibi | to | MFDF, | perform | High | The fused | fast and | Someti | A fused |
| n Yan | provid | Weight | s one- | contrast, | images | efficient | mes | image |
| and | e a fast | map and | level | retain | are more | , and | may not | |
| Zhong | and | guide | image | more | in line | does not | be able | |
| min | efficie | filtering | decomp | edge and | with | have the | to | |
| Li | nt | | osition | texture | human | problem | preserv | |
| | solutio | | and | informati | vision | of | e the | |
| | n for | | generat | on | with high | selectin | edge | |
| | multi- | | es a | | contxxxx | g the | and | |
| | modal | | weight | | xrast. | number | texture | |
| | medica | | map | | | of | informa | |
| | 1 | | which is | | | decomp | tion of | |
| | image | | used to | | | | the | |

| | fusion | | single | | | osition | input | |
|------|---------|----------|----------|-----------|------------|-----------|----------|--------------|
| | in | | fused | | | levels. | images. | |
| | spatial | | image. | | | | | |
| | domai | | | | | | | |
| | n. | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| | | | | | | | | |
| V. | Devel | The | The | The | The | The | The | The fusion |
| AMA | op a | propose | system | method | performa | method | algorith | results |
| LA | hybrid | d hybrid | decomp | focuses | nce of the | claims | m's | obtained |
| RANI | image | image | oses | on | proposed | to retain | effectiv | are |
| AND | fusion | fusion | input | preservin | method is | function | eness in | observed |
| S. | techni | algorith | images | g | claimed | al | medical | and |
| LALI | que | m | using | function | to | informa | imaging | quantitativ |
| THA | that | consists | EMD to | al | demonstr | tion, | tasks | ely |
| KUM | can | of two | extract | informati | ate the | spatial | depends | analysed, |
| ARI | effecti | main | relevant | on while | dominanc | characte | on input | indicating a |
| 2020 | vely | compon | features | maintain | e of the | ristics, | image | favourable |
| | combi | ents: | and then | ing | obtained | and | quality | hybrid |
| | ne the | Empiric | employ | spatial | fusion | produce | and task | fusion |
| | MRI | al mode | s DWT- | character | results. | distortio | context, | response in |
| | and | decomp | based | istics | | n-free | necessit | combining |
| | CT | osition | fusion | from the | | fused | ating | MRI and |
| | images | (EMD) | to | original | | images, | further | CT images |
| | of | and | combin | images | | addressi | research | of the |
| | brain | discrete | e these | without | | ng | for | brain. |
| | to | wavelet | features | introduci | | storage | validati | |
| | provid | transfor | , | ng any | | issues | on | |
| | e high | m | ensurin | distortio | | and | across | |
| | quality | (DWT). | g the | n in the | | offering | diverse | |
| | fused | | retentio | final | | a hybrid | datasets | |
| | images | | n of | | | fusion | and | |

| | with | | function | fused | | approac | addressi | |
|--------|----------|----------|-----------|------------|---|-----------|----------|-------------|
| | no | | al | image. | | h. | ng | |
| | distorti | | details | | | | comple | |
| | on. | | and | | | | X | |
| | | | spatial | | | | comput | |
| | | | characte | | | | ational | |
| | | | ristics | | | | steps | |
| | | | without | | | | and | |
| | | | introduc | | | | practica | |
| | | | ing | | | | 1 | |
| | | | distortio | | | | implem | |
| | | | n into | | | | entation | |
| | | | the | | | | challen | |
| | | | fused | | | | ges. | |
| | | | image. | | | | | |
| Manji | The | it | It uses a | The | _ | The | The | to fuse |
| t Kaur | goal is | consists | multi- | Xception | | multi- | choice | multi- |
| Dilba | to | of a | objectiv | model is | | objectiv | of | modality |
| g | impro | multi- | e | a deep | | e | fusion | medical |
| Singh | ve the | objectiv | differen | neural | | differen | function | images to |
| 2020 | accura | e | tial | network | | tial | s may | obtain a |
| 2020 | cy and | differen | evolutio | that has | | evolutio | affect | more |
| | reliabil | tial | n | been | | n | the | informativ |
| | ity of | evolutio | algorith | shown to | | algorith | perform | e and |
| | medica | n | m to | perform | | m is a | ance of | accurate |
| | 1 | algorith | optimiz | well on | | powerfu | the | representat |
| | imagin | m and | e the | image | | 1 | overall | ion of the |
| | g for | an | weights | classifica | | optimiz | approac | underlying |
| | diagno | Xceptio | of an | tion | | ation | h and | anatomy or |
| | sis and | n | Xceptio | tasks. | | techniq | may | pathology. |
| | treatm | model- | n | Addition | | ue that | require | |
| | ent of | based | model- | ally, we | | can help | extensiv | |
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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 decisionmaking.
- 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 to write and |
| | | Environment | execute the code. |

| 3. | Wavelet Transforms | Used for fusion process | Wavelet transforms is used |
|----|----------------------|-------------------------|----------------------------|
| | | | to capture and fuse |
| | | | components. |
| 4. | Convolutional Neural | Used for classification | The CNN model is trained |
| | Network | | 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 : PyCharm, Visual Studio Code, or Jupyter Notebook.

Environment

• 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.

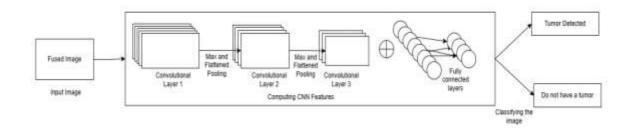


Figure 1: CNN Architecture

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.

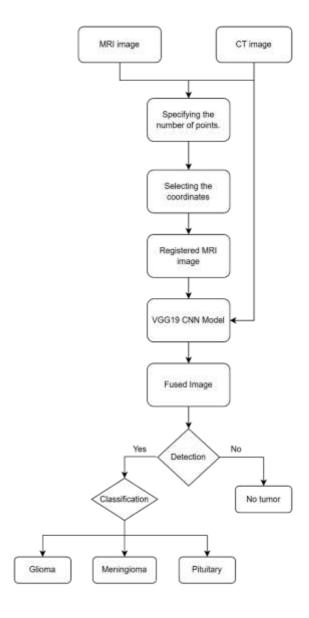


Figure 2: Proposed Architecture

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.

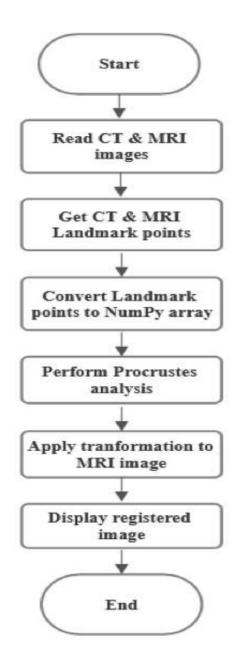


Figure 3: Workflow of Image Registration process

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-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.

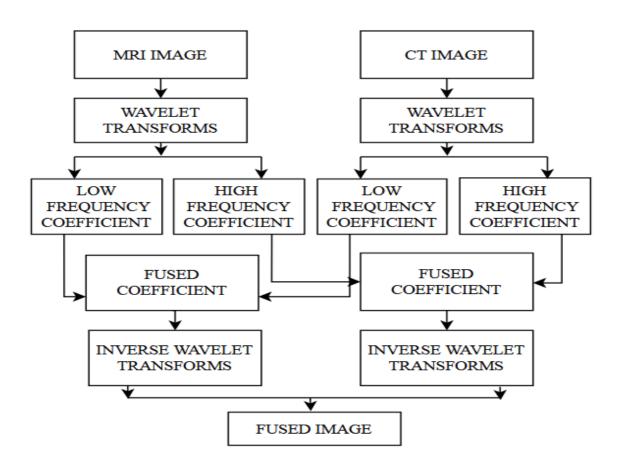


Figure 4: Workflow of Image Fusion

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.

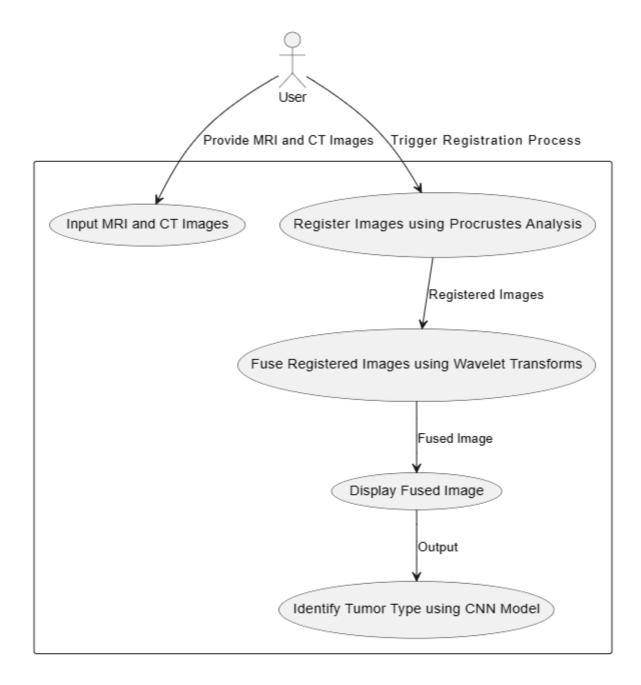


Figure 5: Use case Diagram

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.

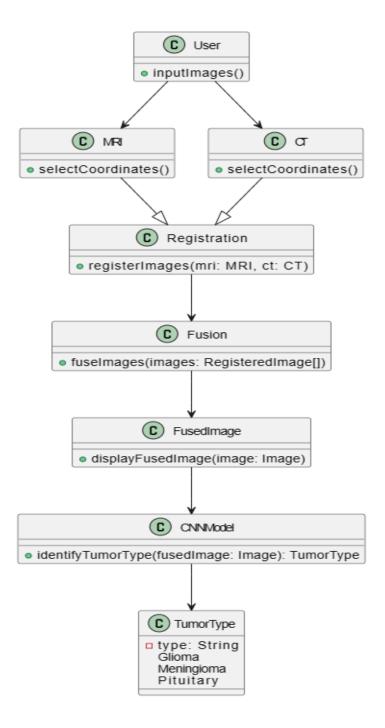


Figure 6: Class Diagram

4.3.3 Sequence Diagram

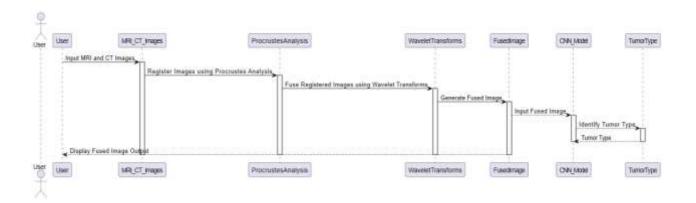


Figure 7: Sequence Diagram

4.3.4 Activity Diagram

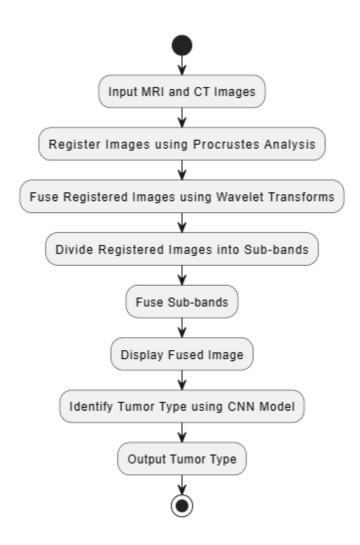


Figure 8: Activity Diagram

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)
  \overline{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} = cv_{2.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())
            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
                 cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-
mri image =
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
                 cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/multimodal-
ct_image
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_'+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()
# Calling the methods for Siamese on LL Images
input_images = []
mri
cv2.imread('C:/Users/sivav/OneDrive/Documents/Final year proj/Testing phase/Testing MRI1
1_{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_fusio
n_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_MRI1
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 fusio
n_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_MRI1
1_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_fusio
n_2.jpg', fusion_img)
# Calling the methods for Siamese on LD Images
input_images = []
cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_MRI1
1_3.jpg')
mri = cv2.cvtColor(mri, cv2.COLOR BGR2GRAY)
ct
cv2.imread('C:/Users/sivav/OneDrive/Documents/Final_year_proj/Testing_phase/Testing_CT11
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_fusio
n_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,
                                                         padding="same",
                                                                              activation="relu",
                                   kernel size=(3,3),
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 \text{ for } i \text{ 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

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>
                                    style="border:4px
                                                         solid
                                                                  Gray;"><font
                                                                                   size="6"
                             <p
style="background:MediumSeaGreen;">Providing
                                                          Comprehensive
                                                                                    Medical
Solutions</font>
    </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"</pre>
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"</pre>
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">
      <br/>
<br/>
<br/>
dockquote class="blockquote">
         <font size="6">"The art of medicine consists of amusing the patient
while nature cures the disease." - Voltaire</font>
      </blockquote>
    </div>
  </div>
  <script src="https://code.jquery.com/jquery-3.4.1.slim.min.js"</pre>
                                                                         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"</pre>
                                                                         integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
    crossorigin="anonymous"></script>
  <script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"</pre>
                                                                         integrity="sha384-
wfSDF2E50Y2D1uUdj0O3uMBJnjuUD4Ih7YwaYd1iqfktj0Uod8GCExl3Og8ifwB6"
    crossorigin="anonymous"></script>
</body>
</html>
```

registration.html

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

{% block link %}

link

href="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/css/bootstrap.min.css"

integrity="sha384-Vkoo8x4CGsO3+Hhxv8T/Q5PaXtkKtu6ug5TOeNV6gBiFeWPGFN9MuhOf23Q9Ifjh"

crossorigin="anonymous">

k url_for('static',filename='css/registration.css') }}">
```

```
{% endblock %}
{% block script %}
<script src="https://code.jquery.com/jquery-3.4.1.min.js"</pre>
               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"</pre>
                                                                          integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
  crossorigin="anonymous"></script>
<script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"</pre>
                                                                          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:</pre>
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"</pre>
```

```
style="border:2px solid #87857f;padding:15px; border-radius:10px;">
           <div>
             MRI X:<span id="mriX"></span>
             MRI Y:<span id="mriY"></span>
           </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-</pre>
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"</pre>
             style="border:2px solid #87857f;padding:15px; border-radius:10px;">
           <div>
             CT X:<span id="ctX"></span>
             CT Y:<span id="ctY"></span>
           </div>
         </div>
      </div>
    </div>
    <div class="row">
      <div class="col-lg-12">
         <center>
           <button onclick="sendParameters()" class="btn btn-primary" style="margin-bottom:</pre>
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>
```

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">
  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"</pre>
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"</pre>
              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"</pre>
                                                                        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"</pre>
                                                                        integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
    crossorigin="anonymous"></script>
  <script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"</pre>
                                                                        integrity="sha384-
wfSDF2E50Y2D1uUdj0O3uMBJnjuUD4Ih7YwaYd1iqfktj0Uod8GCExl3Og8ifwB6"
    crossorigin="anonymous"></script>
</body>
</html>
```

fusion.html

```
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"</pre>
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"</pre>
              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-</pre>
blink" class="load-animation-link">
            </form>
         </center>
       </div>
    </div>
  </div>
  <script src="https://code.jquery.com/jquery-3.4.1.slim.min.js"</pre>
                                                                           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"</pre>
                                                                           integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
    crossorigin="anonymous"></script>
  <script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"</pre>
```

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">
  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</pre>
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"</pre>
                                                                        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"</pre>
                                                                        integrity="sha384-
Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
    crossorigin="anonymous"></script>
  <script src="https://stackpath.bootstrapcdn.com/bootstrap/4.4.1/js/bootstrap.min.js"</pre>
                                                                        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 {
  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);
```

```
.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);
    transform: translateX(5px);
.btn-primary:hover {
  background-color: green;}
```

CHAPTER 6

RESULTS

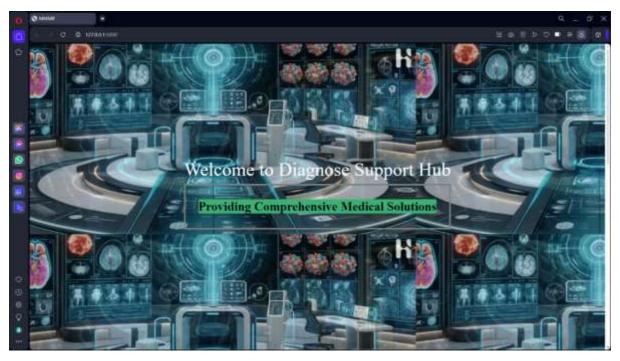


Figure 9: Website Home page

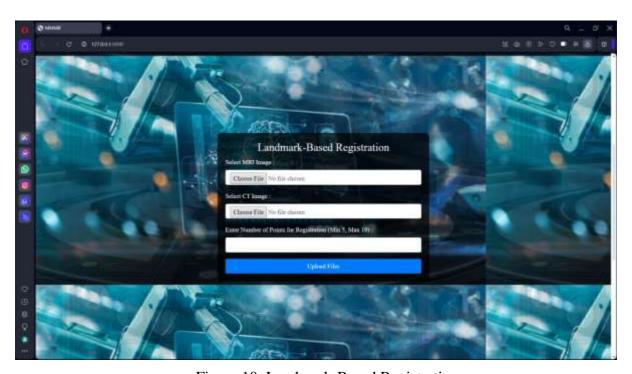


Figure 10: Landmark-Based Registration



Figure 11: Selecting Co-ordinates for Registration Process

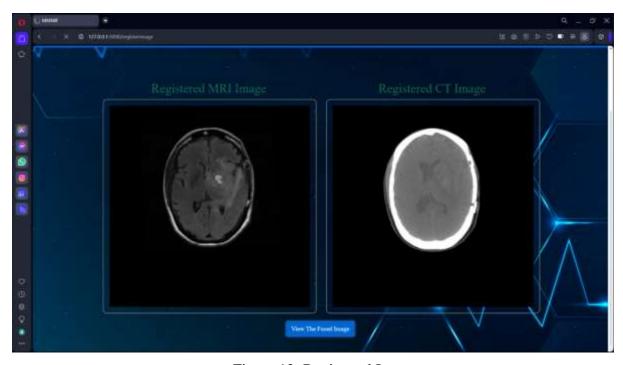


Figure 12: Registered Image



Figure 13: Fused Image

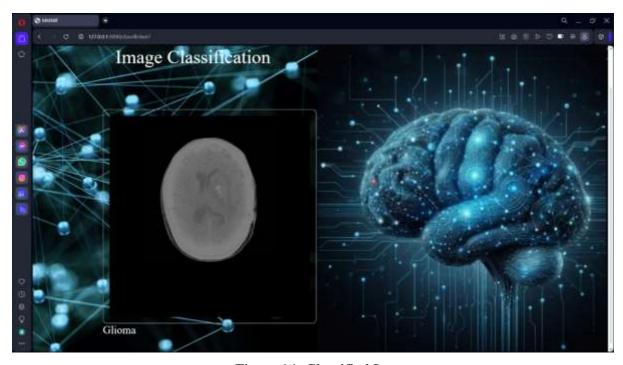


Figure 14: Classified Image

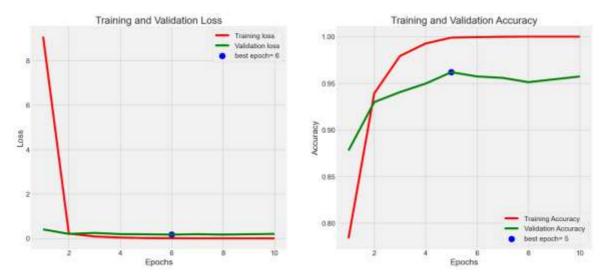


Figure 15: Proposed Model Loss and Accuracy

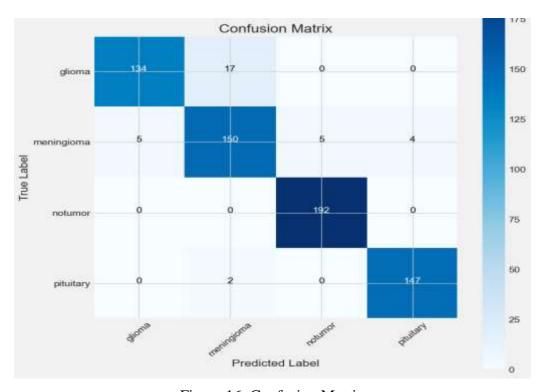


Figure 16: Confusion Matrix

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| gliona | 8.96 | 0.89 | 0.92 | 151 |
| meningiona | 0.89 | 0.91 | 0.90 | 164 |
| notumor | 8.97 | 1.00 | 8.99 | 192 |
| pituitary | 0.97 | 8.99 | 0.98 | 149 |
| accuracy | | | 8.95 | 656 |
| macro avg | 0.95 | 8.95 | 0.95 | 656 |
| weighted avg | 0.95 | 8.95 | 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.